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CRISIS RESPONSE AND STRUCTURAL TRANSFORMATION IN CHINESE INSURANCE COMPANIES: AN INTEGRATED ANALYSIS OF EFFICIENCY AND PRODUCTIVITY

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CRISIS RESPONSE AND STRUCTURAL TRANSFORMATION IN CHINESE INSURANCE COMPANIES: AN INTEGRATED ANALYSIS OF EFFICIENCY AND PRODUCTIVITY

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ABSTRACT

Systematic comparative analysis still lacks understanding how organizational characteristics moderate Chinese insurers' efficiency-productivity evolution across three qualitatively different successive crises. This comprehensive study systematically measures technical and scale efficiency decomposition, analyzes dynamic productivity changes, evaluates efficiency-productivity interactions, and investigates structural business model transformations across fifteen major Chinese insurance companies during three distinct economic crisis periods. Using balanced panel data from 2006 to 2023, it applies four complementary quantitative methods. Data Envelopment Analysis (DEA) distinguishes between technical, pure technical, and scale efficiency. The Malmquist Productivity Index measures changes in total factor productivity over time. A Difference-in-Differences (DID) design isolates the heterogeneous effects of each crisis. Stochastic Frontier Analysis (SFA) identifies time-varying structural sources of inefficiency. Results show that average overall efficiency fell from 0.969 to 0.930 during the Global Financial Crisis but rose slightly from 0.953 to 0.956 during COVID-19, indicating insurance companies learned from past experiences and accelerated digital transformation. In the post-COVID period, total factor productivity grew 2.3% annually, with 72% of improvement coming from technological advancement rather than companies becoming more efficient with existing methods. DID analysis shows digitally-focused, privately-owned firms suffered 4.5 percentage points less efficiency loss compared to others. State-owned firms enjoyed 3.7 percentage points resilience advantage. Both findings were statistically significant, supporting the theory that government ownership provides protective buffer during crises. Further analysis reveals companies with stronger financial positions and more independent boards reduced crisis-related inefficiency by approximately 9% and 6%. This pioneering multi-crisis study revolutionizes insurance resilience understanding by revealing how organizational DNA shapes survival across market upheavals. It delivers breakthrough practical playbooks for executives, ownership-tailored regulatory blueprints for policymakers, while pioneering dynamic efficiency frameworks that extend established theories for emerging markets.

Keywords: Efficiency; Productivity; Crisis resilience; Digitalisation; Data envelopment analysis

ABSTRAK

Kajian perbandingan yang sistematik masih belum memahami bagaimana ciri-ciri syarikat mempengaruhi perubahan kecekapan dan produktiviti syarikat insurans China semasa menghadapi tiga krisis ekonomi yang berbeza. Kajian menyeluruh ini secara sistematik mengukur komponen kecekapan teknikal dan skala, menganalisis perubahan dinamik produktiviti, menilai hubungan antara kecekapan dan produktiviti, serta menyiasat perubahan struktur model perniagaan bagi lima belas syarikat insurans utama China. Berdasarkan data panel seimbang bagi tempoh 2006 hingga 2023, kajian ini menggunakan empat metodologi kuantitatif yang saling melengkapi. *Data Envelopment Analysis* (DEA) membezakan antara kecekapan teknikal, kecekapan teknikal tulen dan kecekapan skala. Indeks Produktiviti Malmquist mengukur perubahan dalam *Total-Factor Productivity* (TFP) mengikut masa. Reka bentuk *Difference-in-Differences* (DID) mengasingkan kesan heterogen bagi setiap krisis. *Stochastic Frontier Analysis* (SFA) mengenal pasti punca struktur ketidakcekapan yang berubah mengikut masa. Keputusan menunjukkan purata kecekapan keseluruhan menurun daripada 0.969 kepada 0.930 semasa Krisis Kewangan Global tetapi meningkat sedikit daripada 0.953 kepada 0.956 semasa COVID-19. Ini menunjukkan syarikat insurans telah belajar daripada pengalaman lepas dan mempercepatkan transformasi digital mereka. Dalam tempoh selepas COVID-19, produktiviti faktor menyeluruh meningkat 2.3% setiap tahun, dengan 72% peningkatan datang daripada kemajuan teknologi berbanding syarikat yang menjadi lebih cekap dengan kaedah sedia ada. Analisis menunjukkan syarikat milik swasta yang memfokuskan teknologi digital mengalami kerugian kecekapan 4.5 mata peratusan lebih kecil berbanding lain. Syarikat milik kerajaan menikmati kelebihan daya tahan 3.7 mata peratusan. Kedua-dua dapatan signifikan secara statistik dan menyokong teori bahawa pemilikan kerajaan memberikan perlindungan semasa krisis. Analisis lanjut mendedahkan syarikat dengan kedudukan kewangan kukuh dan lembaga pengarah bebas mengurangkan ketidakcekapan berkaitan krisis 9% dan 6%. Kajian perintis tiga krisis besar ini mengubah cara kita memahami ketahanan syarikat insurans. Ia mendedahkan bagaimana ciri-ciri syarikat mempengaruhi keupayaan bertahan semasa krisis pasaran. Kajian ini menyediakan panduan praktikal untuk pengurus eksekutif dan rangka kerja kawal selia untuk penggubal dasar, sambil membangunkan teori baharu untuk pasaran membangun.

Kata kunci: Kecekapan; Produktiviti; Daya tahan krisis; Pendigitalan; Analisis Penyampulan Data

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LIST OF ABBREVIATIONS

AXA	AXA Group
BCC	Banker, Charnes and Cooper Model
CBIRC	China Banking and Insurance Regulatory Commission
CCB	China Construction Bank
CCB Life	CCB Life Insurance Co., Ltd.
CCR	Charnes, Cooper and Rhodes Model
China Life	China Life Insurance Company Limited
China Life Group	China Life Insurance (Group) Company
CIRC	China Insurance Regulatory Commission
CNY	Chinese Yuan
CPIC	China Pacific Insurance Company
CPIC Group	China Pacific Insurance (Group) Co., Ltd.
CPIC Life	China Pacific Life Insurance Co., Ltd.
CRS	Constant Returns to Scale
C-ROSS I	China Risk-Oriented Solvency System
C-ROSS II	China Risk-Oriented Solvency System Phase II
DEA	Data Envelopment Analysis
DMU	Decision Making Units
DID	Difference-in-Differences
TEC	Technical Efficiency Change
GDP	Gross Domestic Product
GFC	Global Financial Crisis
ICBC	Industrial and Commercial Bank of China
ICBC-AXA Life	ICBC-AXA Life Insurance Co., Ltd.
VRS	Variable Returns to Scale
Malmquist TFP Index	Malmquist Total Factor Productivity Index
NCI	New China Life Insurance Co., Ltd.
OE	Overall Efficiency
PTC	Pure Technical Efficiency
PICC Group	People's Insurance Company (Group) of China Limited
PICC Life	PICC Life Insurance Company Limited
PICC P&C	PICC Property and Casualty Company Limited

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Ping An Group	Ping An Insurance (Group) Company of China, Ltd.
Ping An Life	Ping An Life Insurance Company of China, Ltd.
Ping An P&C	Ping An Property & Casualty Insurance Company of China, Ltd.
P&C	Property and Casualty
RMB	Renminbi (Chinese Yuan)
Taikang Group	Taikang Insurance Group Co., Ltd.
Taiping Life	Taiping Life Insurance Co., Ltd.
SEC	Scale Efficiency Change
SE	Scale Efficiency
TC	Technical Progress Change
TE	Technical Efficiency
TFP	Total Factor Productivity

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The global financial landscape has been shaped by three major crises over the past two decades, each presenting unique challenges to the insurance sector. The Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19 pandemic (2020-2022) have tested insurance companies' resilience and adaptability in unprecedented ways, particularly in China's evolving market environment. These successive crises have highlighted the varying responses of insurance companies based on their ownership structures and organizational sizes, providing valuable insights into the industry's adaptation mechanisms and resilience patterns.

Among these crises, the emergence of the COVID-19 pandemic in late 2019 has presented particularly complex challenges to companies and economies worldwide (As-Salafiyah, 2023). As nations implemented containment measures such as lockdowns, travel restrictions, and social distancing policies to curb the spread of the virus, significant disruptions occurred across various sectors, affecting both business operations and consumer activities (Nair, 2021). The insurance industry, particularly in China, has experienced substantial impacts within this global context, with effects varying notably across different ownership structures and company sizes (Wu et al., 2022).

The pandemic's impact has manifested through multifaceted challenges to the insurance sector, including business interruptions, increased claims, and declining revenues. The broader economic turmoil during the pandemic, characterized by slowed GDP growth

and rising unemployment rates, has affected insurance companies differently based on their organizational characteristics (Louaas & Picard, 2023). Central state-owned enterprises have demonstrated different response patterns compared to joint-stock companies, while companies of varying sizes have shown distinct adaptation capabilities. These impacts have significantly influenced key performance indicators of insurance companies, particularly their efficiency and productivity metrics, though the extent and specific details of these effects vary across organizational types (Wu et al., 2022; Zeng et al., 2021).

1.2 The Chinese Insurance Market

China's insurance sector has transformed into a global financial powerhouse, becoming the world's second-largest insurance market by 2020 with premium income reaching RMB 4.5 trillion and market penetration of 4.5% of GDP. This evolution has been profoundly shaped by three major economic crises, each accelerating structural changes within the industry.

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The market exhibits a distinctive dual ownership structure: traditional state-owned enterprises leverage government support and established market positions, while increasingly competitive joint-stock companies bring operational flexibility and market responsiveness. This creates a dynamic ecosystem where different organizational forms contribute complementary competitive advantages (Huo et al., 2024; Zhang & Li, 2022).

Company size further diversifies the landscape, with large central state-owned insurance companies utilizing extensive networks to maintain market leadership, medium-sized companies effectively balancing efficiency with responsiveness, and smaller insurance companies excelling in specialized niches. This organizational

diversity has proven critical to the sector's resilience during economic turbulence (Wang et al., 2023; Zhang & Li, 2022).

Beyond commercial operations, the insurance industry serves as a cornerstone of China's financial infrastructure. Through risk protection mechanisms and long-term capital accumulation, it provides essential funding for the real economy while promoting broader financial stability. During crisis periods, this structural diversity becomes particularly valuable—state-owned companies deliver stability through government backing while joint-stock companies demonstrate market adaptability; larger firms leverage resource advantages while medium and smaller companies utilize operational flexibility and specialized positioning to navigate challenges (Xie, 2022).

China’s total premium income grew from RMB 702.6 billion in 2007 to RMB 970.4 billion in 2008, though the growth rate decelerated from 25.8 % to 13.1 % during the Global Financial Crisis (CIRC, 2009). The Chinese Stock-Market Crash wiped approximately RMB 24 trillion in market capitalisation, while premium growth fluctuated between 17.5 % and 20.0 % (CBIRC, 2016). COVID-19 reduced premium growth from 12.2 % in 2019 to 6.1 % in 2020, yet online channels’ share jumped from about 9 % in 2019 to 28.5 % in 2022. Insurance density rose from USD 147 (2009) to USD 351 (2020), illustrating both vulnerability and adaptation across crises. Ownership composition also shifted: central state-owned enterprises’ market share fell from roughly 65 % (2008) to 48 % (2022), whereas joint-stock insurers climbed from 25 % to 35 %. These contrasts motivate a granular assessment of efficiency responses across crisis types.

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This multifaceted structure has enabled China's insurance sector to maintain its essential economic functions during market disruptions while continuing its trajectory of sophisticated integration with national economic development.

1.3 Insurance companies in China

China's insurance sector has demonstrated remarkable growth trajectory, with total assets reaching RMB 27,146.747 billion by end-2022 (9.08% year-on-year growth) and premium income of RMB 4695.70 billion (4.58% increase). This expansion is intrinsically linked to China's broader economic development (Yang, 2024).

The industry's resilience through three major crises reveals its adaptive capacity. During the Global Financial Crisis (2007-2008), the sector experienced dramatic volatility, with growth rates peaking above 40% before sharply declining to approximately 15%. The Chinese Stock Market Crisis (2014-2015) triggered another period of instability, with growth rates fluctuating between 20-30%. Despite these challenges, the industry maintained asset expansion throughout both crises.

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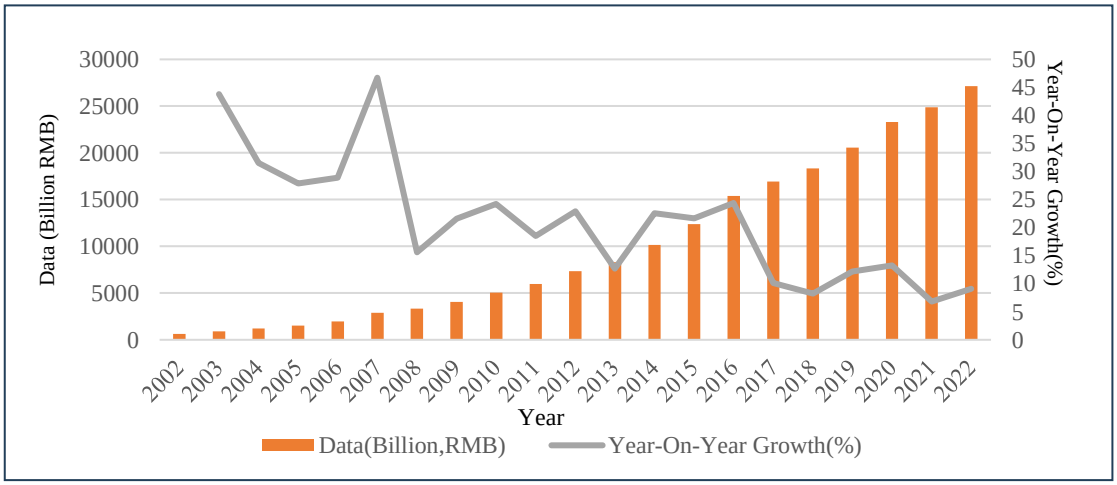


Figure 1.1
Total assets of the Chinese insurance industry from 2002 to 2022
Source: China Insurance Regulatory Commission (CIRC) Annual Report

The COVID-19 pandemic delivered a significant but less severe impact. While asset growth continued, premium income was substantially affected—falling from 12.18% growth pre-pandemic to 6.13% in 2020, then plunging to -0.79% in 2021 before a modest recovery to 4.58% in 2022 (Figure 1.2). Remarkably, total asset growth remained positive at 13.29% in 2020 despite operational disruptions, demonstrating the sector's structural resilience.

China's insurance landscape comprises three primary organizational types: state-owned insurance companies leveraging strong capital and policy support; bank/enterprise-sponsored companies utilizing parent institutions' customer bases; and foreign-funded firms introducing advanced management practices (Shasha, 2023; Zhou et al., 2024). This diverse ecosystem faces intensifying challenges from digital disruptors like ZhongAn Online and stricter regulatory frameworks through the China Risk Oriented Solvency System (Infantino, 2024; Wang, 2023).

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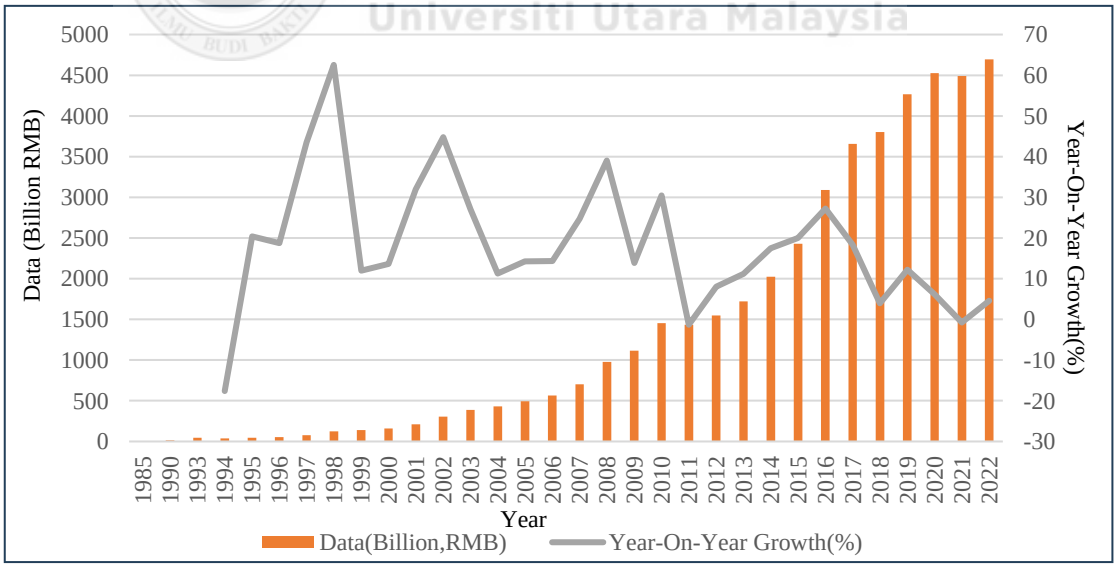


Figure 1.2
Insurance Premium Income in China Nationwide
Source: China Insurance Regulatory Commission (CIRC) Annual Report

While previous research has examined efficiency improvements during 2009-2013 (Li et al., 2023), comprehensive analysis of COVID-19's impact on sector productivity remains underdeveloped (Sun, 2023), highlighting the critical importance of enhancing efficiency metrics in this increasingly competitive and regulated environment.

1.4 Problem Statement

Despite having become the world's second-largest insurance market, China still lacks a systematic understanding of how firm-level efficiency and productivity evolve when successive crises reshape macro-financial conditions. Existing studies tend to focus on single shocks or to treat productivity as a static construct, thereby overlooking (i) the compound effects of three qualitatively different crises and (ii) the transformative surge in digital adoption and mixed-ownership reform after COVID-19 (Zhang, 2024; Liu & Shen, 2023). Consequently, regulators and corporate strategists remain uncertain whether the same determinants drive resilience before, during and after crises of dissimilar origin.

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Previous research has examined isolated aspects of insurance efficiency in China (Li et al., 2023), but fails to provide comparative analysis of productivity evolution across multiple crisis periods. Earlier studies report substantial efficiency declines during the GFC and a modest rebound post-COVID-19(Huang et al., 2022; Kweh et al., 2014; Shieh et al., 2020). The interactions between Technical Efficiency (TE) and Total Factor Productivity (TFP) remain insufficiently explored, particularly regarding how technological changes versus efficiency changes contribute differently during various crisis types. Moreover, existing studies have not adequately quantified the heterogeneous effects of crises across different insurance company characteristics, leaving crucial patterns in organizational resilience unidentified (C. Liu et al., 2023).

This research gap extends to understanding structural changes in efficiency determinants and business models before, during, and after crisis periods. The accelerating digital transformation in the sector—especially following COVID-19—has created new operational paradigms whose relationship to efficiency outcomes remains underexplored. Without this knowledge, both industry stakeholders and policymakers lack the comprehensive insights needed to enhance resilience (Zhang, 2024).

In summary, a clear gap exists at the intersection of (a) the efficiency–productivity–crisis nexus, (b) structural shifts in insurers' business models, and (c) time-varying efficiency determinants. Addressing this gap is pivotal, because the 15 sampled companies—six central state-owned enterprises and nine joint-stock companies—collectively account for about 85 % of national assets and represent the full spectrum of China's organisational forms. Macro-market indicators reveal markedly different stress patterns across the GFC, CSC and COVID-19, and without evidence on how solvency, digital intensity and ownership interact with crisis type, policy makers cannot tailor counter-cyclical capital relief or digital-transition incentives effectively. This study therefore quantifies those relationships and, in doing so, offers actionable guidance for strengthening systemic resilience.

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1.5 Research Questions

The research questions of the study are as follows:

1) How did the technical, pure technical, and scale efficiency of Chinese insurance companies vary during the GFC, CSC, and COVID-19 periods?
2) What were the dynamic changes in productivity of Chinese insurance companies during the GFC, CSC, and COVID-19 periods, and how did technological changes and efficiency changes contribute to these variations?
3) What are the relationships between efficiency and productivity across the GFC, CSC, and COVID-19 periods, and how do these efficiency–productivity interactions differ by insurance-company characteristics?
4) How have the determinants of efficiency and the business models of Chinese insurance companies structurally changed across the GFC, CSC, and COVID-19 periods, with particular emphasis on technological adaptation and operational transformation?

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1.6 Research Objectives

The main objectives of the current study are as follows:

1) To measure and decompose the technical, pure technical, and scale efficiency of Chinese insurance companies during crisis periods (GFC, CSC and COVID-19).
2) To analyze the dynamic changes in productivity, comparing technological changes and efficiency changes across the GFC, CSC, and COVID-19 periods.
3) To evaluate the relationships between efficiency and productivity measures across the GFC, CSC and COVID-19 periods, and to determine how these efficiency–productivity interactions vary by insurance-company characteristics.

4) To investigate the structural changes in efficiency determinants and business models of Chinese insurance companies across major crisis periods, with a particular emphasis on technological adaptation and operational transformation.

1.7 Significance of the Study

This research offers substantial value to multiple stakeholders by addressing crucial knowledge gaps in understanding insurance sector resilience during economic crises. Its significance spans academic, industry, and policy domains.

For academics, this study pioneers a comprehensive methodological approach that integrates efficiency decomposition, productivity analysis, and crisis impact assessment across multiple disruption periods. By establishing empirical relationships between organizational characteristics and crisis resilience, it creates a foundation for more nuanced theoretical frameworks in financial institution performance during market stress.

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For industry practitioners, the findings provide actionable insights into which organizational structures, business models, and operational characteristics offer superior resilience during different crisis types. Insurance executives can leverage these insights to enhance strategic planning, resource allocation, and technological investment decisions. The comparative analysis across three distinct crises offers valuable pattern recognition for anticipating vulnerability points and strengthening adaptive capabilities.

For policymakers and regulators, this research delivers empirical evidence critical for designing more effective regulatory frameworks that balance stability with adaptation capacity. By quantifying how different company types respond to economic shocks, it

enables more targeted and proportionate regulatory approaches that acknowledge the heterogeneous nature of the insurance sector. This supports the development of crisis response mechanisms that enhance systemic resilience while avoiding unnecessary constraints on innovation.

For China's financial system more broadly, understanding insurance sector efficiency during crises strengthens a critical pillar of economic stability. As insurance companies play dual roles in risk absorption and financial intermediation, enhancing their resilience directly contributes to broader economic security and recovery capacity following disruptions.

Finally, this study's significance extends beyond China through its methodological innovations and comparative analysis framework, offering valuable approaches for examining insurance sector efficiency in other emerging economies facing similar challenges of market volatility and increasing crisis frequency in an interconnected global financial system.

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1.8 Scope of the Study

This study examines the efficiency and productivity dynamics of Chinese insurance companies across three major crisis periods: the Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19 pandemic (2020-2022). The research sample comprises 15 major insurance companies, selected based on their market representation and data availability across all three crisis periods. These companies are categorized by ownership structure (central state-owned enterprises and joint-stock companies) and size classification (large, medium, and small), providing a comprehensive view of different organizational types in China's insurance sector.

This comprehensive scope enables the investigation of three major unique contributions: the relationship between efficiency-productivity-crises dynamics, the structural business model changes across different crisis types, and the evolution of efficiency determinants caused by distinct crisis characteristics.

The sample selection focuses particularly on companies that maintained continuous operations throughout the study period (2006-2023), allowing for consistent analysis across all three crises. The selected companies collectively represent approximately 85% of China's insurance market by premium income, ensuring comprehensive market coverage. The sample includes both state-owned enterprises that benefit from strong government support and joint-stock companies that demonstrate greater operational flexibility, enabling comparative analysis across ownership types. Additionally, the varying sizes of selected companies, from large national insurance companies to smaller regional operators, permits examination of how organizational scale influences crisis response patterns.

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Data sources for this study primarily comprise the China Insurance Yearbook, annual reports of insurance companies, and regulatory filings with the China Banking and Insurance Regulatory Commission (CBIRC). These sources provide detailed financial and operational data, including key metrics such as premiums, investment income, claims, and operational costs. The data collection spans from 2006 to 2023, encompassing all three crisis periods and allowing for comprehensive analysis of crisis impacts and recovery patterns across different organizational types. This extended timeframe enables examination of how different types of insurance companies adapt their efficiency and productivity metrics in response to varying forms of market stress.

The scope of analysis focuses on several key dimensions of organizational performance. Technical efficiency measures examine how effectively different types of companies convert inputs into outputs across crisis periods. Scale efficiency analysis investigates how organizational size influences performance during market stress. Productivity metrics assess how different organizational types maintain output generation relative to input utilization during crisis periods. Additional analysis examines structural changes in efficiency determinants across ownership types and company sizes, providing insights into how different organizational forms adapt their business models in response to market disruptions.

The analysis will quantitatively assess these dimensions [referring to efficiency, productivity, and structural changes] using advanced econometric and frontier analysis techniques suitable for panel data, ensuring a robust and multi-faceted examination of crisis impacts.

This comprehensive scope, combining multiple crisis periods, varied organizational types, and diverse analytical approaches, is expected to produce nuanced insights into how different insurance companies maintain performance during periods of market stress. The findings will be particularly relevant for understanding how ownership structure and company size influence organizational resilience and adaptation capabilities in the face of different types of market disruption.

1.9 Definition of Key Terms

The following terms are defined in the context of research and supported by literature review.

Scale Efficiency (SE): Measures whether an insurance company is operating at its optimal size. SE equal to 1 indicates optimal scale operation, while values less than 1 suggest either increasing or decreasing returns to scale (Aparicio & Santín, 2024).

Overall Efficiency (OE) (θ): Represents the comprehensive efficiency of an insurance company, calculated as the product of technical efficiency and scale efficiency. Values range from 0 to 1, with 1 indicating maximum efficiency (Sueyoshi et al., 2023).**Validity:** In DEA analysis, refers to the effectiveness of decision-making units (DMUs), categorized as either DEA-efficient (when efficiency score equals 1 and all slacks are zero) or DEA-inefficient (Ji et al., 2025; Shu & Cai, 2023).

Scale Efficiency Change (SECH): Indicates changes in the scale efficiency of operations over time. Values greater than 1 suggest improved scale efficiency (Bansal & Singh, 2021; Cvetkovska & Peovski, 2022).

Malmquist Productivity Index: A bilateral index that measures productivity changes between two time periods, decomposable into efficiency change and technical change components. This index is particularly useful for analysing panel data in the insurance industry (Esmaeili et al., 2021; Kaya, 2024).

Data Envelopment Analysis (DEA): A non-parametric method used to evaluate the relative efficiency of decision-making units (insurance companies) by constructing a piece-wise linear frontier of best-performing entities (Kumar & P., 2024; Zhang et al., 2023).

Difference-in-Differences (DID): Statistical method comparing changes between treatment and control groups over time (Tchetgen et al., 2024; G. Wang et al., 2024).

1.10 The Organisation of the Study

This thesis is organized into five interconnected chapters that systematically investigate how different types of Chinese insurance companies maintain efficiency and productivity during multiple crisis periods. The organization directly aligns with the research objectives of examining efficiency decomposition, productivity dynamics, crisis impact patterns, and structural transformations across organizational types.

Chapter One introduces the research framework by establishing the context of three major crises (GFC, CSC, and COVID-19) and their varying impacts on central state-owned enterprises and joint-stock companies of different sizes. This chapter presents the background, objectives, significance, and scope of the research, setting the foundation for examining how organizational characteristics influence crisis response patterns.

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Chapter Two provides a comprehensive literature review focusing on three key areas: theoretical frameworks for understanding efficiency and productivity in insurance companies, empirical studies examining crisis impacts across different organizational types, and methodological approaches for analysing performance patterns during market stress. This review identifies critical research gaps in understanding how ownership structure and company size influence crisis resilience.

Chapter Three details the multi-methodological research framework employed to address the research objectives. It explains the application of Data Envelopment Analysis (DEA) for efficiency decomposition, Malmquist Productivity Index for

examining dynamic changes, correlation and Difference-in-Differences (DID) analyses for investigating crisis impacts, and Stochastic Frontier Analysis (SFA) for examining structural transformations. This chapter also outlines the data collection process and analytical procedures across different organizational types and crisis periods.

Chapter Four presents the empirical findings through four distinct analyses aligned with the research objectives: First, it examines efficiency decomposition patterns across organizational types during crisis periods using DEA. Second, it analyzes productivity dynamics through Malmquist index decomposition, comparing technological and efficiency changes across different company types. Third, it investigates crisis impact patterns through correlation and DID analyses, focusing on how organizational characteristics influence performance during market stress. Fourth, it explores structural transformations in efficiency determinants using SFA, examining how different types of insurance companies adapt their business models across crisis periods.

Chapter Five provides a comprehensive discussion of the findings and conclusions. It examines how different organizational characteristics influence crisis resilience and adaptation patterns, comparing results across central state-owned enterprises and joint-stock companies of varying sizes. This chapter synthesizes key findings about how organizational characteristics influence crisis response patterns, discusses research limitations, and provides targeted recommendations for different types of insurance companies. It offers specific insights for enhancing crisis resilience based on ownership structure and company size, while also suggesting directions for future research in understanding organizational adaptation to market stress.

Throughout these chapters, the thesis maintains a consistent focus on how ownership structure and company size influence insurance companies' ability to maintain

efficiency and productivity during different types of market crisis periods. This organizational structure ensures systematic examination of how various types of insurance companies adapt to and recover from major market disruptions, providing valuable insights for both academic understanding and industry practice.

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CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive examination of theoretical and empirical literature pertinent to understanding how different types of insurance companies maintain efficiency and productivity during periods of market stress. The review spans three major crises affecting China's insurance sector: the Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19 pandemic (2020-2022). Particular attention is paid to how organizational characteristics - specifically ownership structure (central state-owned enterprises versus joint-stock companies) and company size (large, medium, and small) - influence crisis response patterns and recovery capabilities.

The literature review is structured around four key themes that directly align with the research objectives. First, it examines theoretical frameworks related to efficiency measurement and decomposition, focusing particularly on how different organizational types maintain operational effectiveness during crisis periods. Second, it explores productivity theory and empirical research on how ownership structure and company size influence adaptation capabilities across different forms of market stress. Third, it investigates literature on crisis impacts and organizational responses, with specific attention to how different types of insurance companies maintain performance during market disruptions. Fourth, it examines research on structural transformations in the insurance sector, focusing on how different organizational types adapt their business models in response to market challenges.

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This chapter lays the theoretical and empirical foundation for examining how organizational characteristics influence insurance companies' ability to maintain efficiency and productivity during crisis periods. The insights drawn from this literature review inform the research methodology and provide context for interpreting the study's findings about crisis impacts across different organizational types. In line with this purpose, Section 2.3 synthesises theoretical and qualitative insights, while Section 2.4 reviews quantitative empirical evidence on China’s insurance market.

2.2 Theoretical Framework

This section presents the integrated theoretical foundation for examining efficiency and productivity in Chinese insurance companies during three major crisis periods: the Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19 pandemic (2020-2022). Ten complementary theoretical perspectives provide the conceptual basis for addressing the research objectives established in Chapter One.

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2.2.1 X-Efficiency Theory

X-Efficiency Theory, introduced by Leibenstein (1966), provides a fundamental framework for understanding efficiency variations among organizations with similar resources and market conditions. Unlike conventional microeconomic theories that assume firms automatically maximize outputs given their inputs, X-Efficiency Theory recognizes that firms often operate below their theoretical production possibilities frontier due to behavioural and organizational factors (Perelman, 2011).

The theory identifies several sources of efficiency gaps: managerial inefficiency from suboptimal decision-making, organizational slack resulting from incomplete contracts,

motivational inefficiency when stakeholders lack sufficient incentives, and knowledge utilization gaps when best practices are incompletely implemented. These factors directly support the first research objective, which seeks to measure and decompose technical, pure technical, and scale efficiency during crisis periods (Polo-Garrido & Vargas-Ulloa, 2024).

In the insurance context, X-Efficiency Theory explains why efficiency components may vary significantly across companies facing similar external pressures. During crisis periods, competitive pressures may compel firms to reduce inefficiencies as a survival mechanism, while organizations with superior internal incentive structures may maintain higher efficiency levels despite market turbulence (Giantsios & Noulas, 2019). This theoretical lens provides the foundation for decomposing efficiency into its constituent components using Data Envelopment Analysis (DEA).

This theory provides the foundation for understanding efficiency decomposition in the conceptual framework, explaining how organizational and environmental factors create gaps between actual and optimal performance during crisis periods.

2.2.2 Resource-Based View

Resource-Based View (RBV), formalized byBarney (2001), explains how organizational characteristics influence performance outcomes through resource heterogeneity. The theory posits that firms possess unique resource bundles that vary in their value, rarity, imitability, and organizational embeddedness (VRIO framework), creating differential capacities to withstand external shocks (W. Sun et al., 2024).

This perspective directly supports the first research objective by explaining how company size might influence efficiency decomposition during crises. In the insurance

industry, RBV suggests that larger companies typically benefit from resource advantages—including financial reserves, diversified portfolios, and advanced risk management systems—that can buffer operational disruptions. However, these same organizations may face rigidities in scale optimization when markets change rapidly, creating potential scale efficiency vulnerabilities (Arbelo et al., 2021).

RBV provides crucial insights for interpreting efficiency differences across companies of varying sizes when analyzing technical, pure technical, and scale efficiency components. The theory suggests that resource configurations significantly influence how companies maintain operational effectiveness during market stress, with implications for understanding heterogeneous efficiency patterns across the insurance sector (Moradi et al., 2021).

This theory supports the moderating role of organizational characteristics in the conceptual framework, explaining how resource heterogeneity influences crisis resilience across different company types.

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2.2.3 Total Factor Productivity Theory

Total Factor Productivity (TFP) Theory, pioneered by Solow (1957) and extended to financial institutions by Färe et al. (1994), provides the framework for analyzing dynamic productivity changes during crisis periods. The theory posits that output growth stems not only from increased input utilization but also from technological progress and efficiency improvements, captured through the production function $Y = A \times F(K, L)$, where A represents productivity independent of input growth (Chang et al., 2024; Rehman & Islam, 2023).

This theoretical perspective directly addresses the second research objective, which aims to analyse dynamic productivity changes and compare technological changes and efficiency changes across crisis periods. TFP Theory suggests that different crisis environments create varying incentives for productivity improvements: market crises typically constrain technological investment while increasing pressure for operational efficiency, while operational crises may accelerate technological adoption (Furceri et al., 2021; Wang et al., 2020).

By employing the Malmquist Productivity Index decomposition method, which builds upon Solow's framework, researchers can separate productivity changes into efficiency change (catching up to the frontier) and technological change (frontier shifts) components. This decomposition provides nuanced insights into adaptation mechanisms across different crisis environments, supporting comprehensive analysis of how productivity evolves through periods of market stress (Esmaeili et al., 2021; Yu et al., 2021).

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This theory underpins the productivity outcomes component in the conceptual framework, providing the theoretical basis for decomposing productivity changes into efficiency and technological progress elements.

2.2.4 Institutional Theory and Public Choice Theory

Institutional Theory by DiMaggio and Powell (1983) and Powell and Public Choice Theory by Dewenter and Malatesta (2001) provide complementary perspectives on how ownership structure influences organizational behavior during crisis periods. These theories directly support the second research objective by explaining how ownership characteristics might affect productivity dynamics across different types of market disruption (Ferrero, 2020; Karbhari et al., 2020).

Institutional Theory examines how organizational structures and behaviors are shaped by institutional environments rather than purely economic considerations. The theory identifies three mechanisms of institutional isomorphism—coercive, mimetic, and normative—that drive organizations toward similar practices within institutional fields. In the Chinese insurance market, this theory suggests that state-owned companies operate within distinct institutional frameworks characterized by different government connections, regulatory expectations, and performance metrics compared to joint-stock companies (Dua, 2022).

Public Choice Theory complements this perspective by explaining how ownership structure influences managerial incentives and decision-making processes. The theory suggests that state-owned enterprises operate with different objective functions than private firms due to political considerations and bureaucratic influences. Managers in state-owned insurance companies may prioritize stability, employment preservation, and policy implementation over profit maximization and technological innovation during market disruptions (Mengiste, 2020).

Together, these theories suggest that ownership structure significantly influences productivity change patterns during crises. State-owned insurance companies might demonstrate stronger efficiency stability due to institutional support and reduced profit pressures but face potential constraints in technological innovation due to bureaucratic decision processes. Joint-stock companies, facing stronger market pressures, might exhibit greater productivity volatility but potentially faster technological adaptation.

These theories explain how ownership structure influences the relationship between organizational characteristics and efficiency outcomes in the conceptual framework, particularly during crisis periods.

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2.2.5 Resource Dependency Theory

Resource Dependency Theory, introduced by Pfeffer and Salancik, as it researched by Hillman et al. (2009), provides the theoretical framework for understanding how external resource relationships influence crisis vulnerability. The theory proposes that organizations develop strategies to manage dependencies on critical resources, and these dependency patterns significantly affect their ability to respond to external disruptions (Ansmann et al., 2021; Hillman et al., 2009).

This theoretical perspective directly supports the third research objective, which examines the relationship between efficiency measures and crisis impacts. Resource Dependency Theory suggests that different crisis types affect various organizational forms differently based on their external resource dependencies. Market-based crises (GFC, CSC) would disproportionately affect organizations with greater dependence on capital markets, while operational disruptions like COVID-19 would present greater challenges for organizations with extensive physical networks and complex coordination requirements (Isik & Uygur, 2021).

The theory identifies several strategies organizations employ to manage resource dependencies during environmental uncertainty, including buffering, bridging, and adaptation. The effectiveness of these strategies varies by organizational type and crisis nature, creating systematic patterns in efficiency-crisis relationships when examined through correlation and difference-in-differences analyses (Coşkun & Öztürk, 2024; Kui et al., 2024). This theoretical lens provides crucial insights for understanding heterogeneous crisis effects across different insurance company characteristics.

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This theory explains the differential crisis impacts shown in the conceptual framework, illustrating how external resource dependencies create systematic vulnerability patterns across organizational types.

2.2.6 Institutional Economic Theory

Institutional Economic Theory, formalized by North (1990), examines how formal and informal institutional arrangements influence economic behavior and organizational performance. The theory proposes that institutions—defined as "the rules of the game" including formal laws, regulations, and informal norms—create incentive structures that shape organizational decisions and adaptation capabilities (Wanjuu & Le Roux, 2017; Xie, 2022).

This theoretical perspective directly supports the third research objective, particularly for examining causal relationships between efficiency measures and crisis impacts through difference-in-differences methodology. Institutional Economic Theory suggests that different institutional arrangements create varying adjustment costs and adaptation capabilities during crisis periods, leading to identifiable patterns in efficiency-crisis relationships across different organizational types.

In the Chinese insurance market, characterized by a mix of state-owned and joint-stock companies operating under evolving regulatory frameworks, this theory helps explain why efficiency-crisis relationships might vary systematically across different segments of the industry. The theory suggests that institutional arrangements create varying capacities to absorb, interpret, and respond to exogenous shocks, directly supporting the analysis of heterogeneous effects across different insurance company characteristics (Gao et al., 2025; G. Liu et al., 2023).

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This theory supports the causal pathways in the conceptual framework, explaining how institutional arrangements influence the efficiency-crisis relationship through transaction cost mechanisms.

2.2.7 Evolutionary Economic Theory and Path Dependency Theory

Evolutionary Economic Theory founded by Nelson and Winter (1985) and Path Dependency Theory which was founded by Arthur (1989) provide complementary perspectives on how organizational capabilities evolve through selection pressures and historical constraints. These theories directly support the fourth research objective, which investigates structural changes in efficiency determinants before, during, and after crisis periods (Jo, 2021; Nelson et al., 2018).

Evolutionary Economic Theory views firms as repositories of routines and capabilities that develop through experiential learning and selection mechanisms rather than instantaneous optimization decisions. The theory suggests that economic shocks create selection environments that favor certain routines and capabilities over others, leading to measurable shifts in how different factors contribute to efficiency across successive crises (Teece, 2023).

Path Dependency Theory complements this perspective by explaining how historical decisions constrain future options through self-reinforcing mechanisms. The theory proposes that organizational trajectories are not freely chosen at each moment but rather are substantially influenced by previous investments, decisions, and institutional arrangements (Stache & Sydow, 2023). This explains why structural changes in efficiency determinants follow specific evolutionary paths rather than optimal jumps.

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Together, these theories suggest that insurance companies' technological capabilities, operational models, and efficiency determinants evolve through incremental adaptations constrained by previous investments. The theories predict measurable structural changes in efficiency determinants across crisis periods, with technological factors gaining importance following each successive crisis as companies adapt their routines to new competitive environments while remaining influenced by their historical development paths.

These theories explain the structural transformation elements in the conceptual framework, showing how crisis experiences reshape efficiency determinants through evolutionary selection processes.

2.2.8 Organizational Learning Theory

Organizational Learning Theory, articulated by Argote and Miron-Spektor (2011), examines how organizations acquire, process, and retain knowledge from experience. The theory proposes that organizations develop capabilities through experiential learning, and these capabilities enhance performance in future similar situations through knowledge retention and application mechanisms (Ghalandari et al., 2023).

This theoretical perspective directly supports the fourth research objective, particularly the emphasis on technological adaptation and operational transformation. Organizational Learning Theory suggests that firms develop crisis management capabilities through direct experience, vicarious learning, and knowledge codification processes, potentially leading to measurable improvements in crisis resilience across successive disruptions (Andres & Heo, 2023).

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The theory distinguishes between several learning mechanisms that organizations employ to develop crisis management capabilities. Experiential learning occurs through direct involvement in crisis management, creating tacit knowledge about effective response strategies. Vicarious learning involves observing other organizations' experiences and outcomes. Knowledge codification transforms tacit crisis management insights into explicit procedures and protocols (Qadri et al., 2024).

These mechanisms suggest that insurance companies that effectively incorporate lessons from previous crises may demonstrate diminishing negative efficiency impacts in successive disruptions. The effectiveness of these learning processes varies by organizational type and institutional context, potentially explaining differential patterns in structural transformations across different segments of China's insurance sector (Ghaderi et al., 2024; Greve, 2024).

This theory explains the feedback mechanisms in the conceptual framework, illustrating how crisis experiences create learning effects that influence future efficiency and productivity patterns.

2.2.9 Integration of Theoretical Perspectives

This study integrates these eight theoretical perspectives to develop a comprehensive understanding of efficiency and productivity dynamics in Chinese insurance companies during crisis periods. Each theory directly supports specific research objectives while contributing to a holistic framework for examining organizational performance during market disruptions.

X-Efficiency Theory and Resource-Based View provide the foundation for examining efficiency decomposition as outlined in the first research objective. Total Factor

Productivity Theory, Institutional Theory, and Public Choice Theory collectively support the analysis of dynamic productivity changes in the second research objective. Resource Dependency Theory and Institutional Economic Theory inform the examination of efficiency-crisis relationships in the third research objective. Evolutionary Economic Theory, Path Dependency Theory, and Organizational Learning Theory provide the theoretical basis for investigating structural transformations in efficiency determinants as outlined in the fourth research objective.

Together, these theories create a robust conceptual framework for analyzing how different types of Chinese insurance companies maintain efficiency and productivity during periods of market stress. This integrated approach acknowledges the multifaceted nature of organizational performance during crises and provides the theoretical foundation for the subsequent development of specific research hypotheses that will be presented in Chapter Three.

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2.3 Literature Review

The literature framework for this study draws upon research examining three major crisis periods affecting China's insurance sector: the Global Financial Crisis (2007-2008), Chinese Stock Market Crisis (2014-2015), and COVID-19 pandemic (2020-2022). This integrated review examines how different types of market stress influence insurance companies' performance, with particular attention to efficiency measurement, productivity analysis, crisis impact assessment, and structural transformation. The comprehensive approach becomes especially relevant when analysing how Chinese insurance companies with varying organizational characteristics respond to and recover from different forms of market disruption.

2.3.1 Theoretical and Methodological Foundations

Research on insurance efficiency and productivity during crisis periods has evolved significantly, incorporating multiple methodological approaches and theoretical perspectives. Early studies focused primarily on ratio-based performance measures, but recent research has adopted more sophisticated analytical frameworks that capture the complex relationships between organizational characteristics and crisis resilience (Meng, 2021).

2.3.1.1 Evolution of Efficiency Measurement

The measurement of efficiency in insurance during crisis periods has progressed through several methodological phases. Data Envelopment Analysis (DEA) has emerged as a crucial tool for examining crisis-period efficiency, with Kaffash et al. (2020) demonstrating its effectiveness in decomposing performance into technical and scale components. This decomposition proves particularly valuable when examining how different organizational characteristics influence crisis resilience. Xie et al. (2023) extended this analysis by examining how efficiency patterns vary between state-owned and joint-stock insurance companies during market stress, finding that ownership structure significantly influences adaptation capabilities. Recent Chinese studies (Huo et al., 2024; Jin & Chen, 2024; Liu et al., 2020) show that state-controlled insurers provide stronger solvency buffers during crises but lag in cost efficiency during normal periods, while mixed-ownership hybrids recorded the fastest post-COVID rebound in Technical Change (TC). These conflicting findings reveal an unaddressed ownership × crisis interaction, which this study tests in Chapter 4.

The development of DEA applications in insurance research has particularly focused on handling crisis-period complexities. Recent studies have incorporated advanced

DEA variations that account for environmental factors and uncontrollable variables, providing more nuanced insights into how organizational characteristics influence crisis performance (Mahanta et al., 2024). This methodological evolution reflects growing recognition that crisis impacts vary systematically across different types of insurance companies.

2.3.1.2 Productivity Analysis Frameworks

The Malmquist productivity index, developed by Färe et al. (1994) and applied extensively, complements DEA by enabling analysis of productivity changes over time. This methodology has proven particularly valuable for understanding adaptation mechanisms during market stress, as it separates productivity changes into efficiency improvements and technological advancement. Sun (2020) applied this approach to analyze Chinese insurance companies' productivity evolution across multiple crisis periods, revealing distinct patterns of adaptation and recovery between different organizational forms.

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Recent applications of the Malmquist index have specifically focused on crisis-period dynamics. Christopoulos et al. (2022) developed enhanced decomposition approaches that better capture the technological aspects of crisis adaptation, while Shojaie et al. (2024) introduced methodological refinements for analyzing productivity changes during periods of market turbulence. These advances provide more precise tools for examining how different organizational types maintain productivity during crisis periods.

2.3.1.3 Crisis Impact Assessment Methods

Crisis impact studies have increasingly employed sophisticated analytical approaches that go beyond traditional performance metrics. Kaya (2024) conducted comprehensive meta-analysis of efficiency studies, identifying size, ownership structure, and product mix as crucial determinants of performance during market stress. These findings establish important baselines for examining how crisis impacts vary across different organizational characteristics. Yu et al. (2021) demonstrate significant geographical variations in Chinese insurance market performance, highlighting the importance of regional factors in crisis response patterns.

Recent methodological developments have particularly focused on isolating crisis effects from other performance determinants. Difference-in-differences approaches have gained prominence, with studies like C. N. Wang et al. (2024) employing these methods to identify causal effects of crisis events on insurance company performance. This methodological evolution reflects growing recognition of the need to distinguish crisis impacts from other factors affecting organizational performance.

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2.3.1.4 Regulatory Environment Analysis

The regulatory environment significantly shapes crisis responses in the insurance sector. Regele and Gründl (2024) examined how Chinese insurance companies responded heterogeneously to solvency regulation changes, providing crucial insights into the relationship between regulatory frameworks and operational efficiency during market stress. They further explored this theme by analyzing how regulatory requirements influenced crisis adaptation strategies across different types of insurance companies, finding that regulatory frameworks significantly affect both the speed and effectiveness of crisis response mechanisms.

Recent studies have particularly focused on how regulatory environments influence crisis adaptation capabilities. Ige-Gbadeyan and Swanepoel (2023) demonstrated that regulatory frameworks significantly affect insurance companies' ability to maintain operational efficiency during market stress, while Nasri et al. (2024) showed how regulatory requirements shape technological adoption patterns during crisis periods. These findings highlight the importance of considering regulatory contexts when analyzing crisis impacts across different organizational types.

Firm-size evidence is likewise mixed. Wu et al. (2022) finds scale economies among large life insurers, whereas Zhou et al. (2020) and Ouyang et al. (2024) report faster TC gains for medium-sized non-life specialists during the CSC. How size and crisis jointly affect productivity therefore remains an open question addressed later in this study.

2.3.2 Crisis Impact and Market Evolution

Research examining specific crisis periods has revealed distinct impact patterns across the insurance sector. These studies provide valuable insights into how different types of market stress affect insurance company performance and how organizational characteristics influence crisis resilience.

2.3.2.1 Global Financial Crisis Impact

Studies examining the Global Financial Crisis have revealed significant variations in impact patterns across different types of insurance companies. Hassan (2022) analyzed the 2008 financial crisis effects, highlighting significant variations between life and non-life sectors and demonstrating how organizational characteristics influenced crisis vulnerability. These findings provide important comparative insights for understanding how different insurance segments respond to market stress.

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Recent research has particularly focused on the long-term implications of GFC experiences. Goosman (2022) examined how insurance companies' crisis management capabilities evolved following the GFC, while Galaieva et al. (2021) analysed how ownership structure influenced post-crisis recovery patterns. These studies suggest that GFC experiences significantly shaped subsequent crisis management approaches across the insurance sector.

2.3.2.2 Market Structure Evolution

Research on market structure evolution has revealed important trends in how insurance companies adapt to crisis conditions. Wang and Makarenko (2021) observed significant untapped potential in China's life insurance industry under "new normal" conditions, suggesting opportunities for efficiency improvement even during challenging market conditions. Wu et al. (2022) extended this analysis to the COVID-19 period, demonstrating how different types of insurance companies adapted their operational models to maintain efficiency during unprecedented market disruption.

Studies have particularly focused on how market structure influences crisis resilience. Zhou et al. (2024) examined how market concentration affects crisis adaptation capabilities, while Zheng et al. (2021) analysed how market position influences technological adoption during crisis periods. These findings highlight the importance of considering market structure when analysing crisis impacts across different organizational types.

2.3.2.3 Technological Transformation

Technological advancement has emerged as a crucial factor in crisis adaptation. Wang (2023) demonstrated how technological innovation influenced operational efficiency during market stress, particularly in claims management and cost control. This

technological dimension becomes especially relevant when examining how insurance companies maintain operational effectiveness during periods of market disruption.

Recent studies have specifically focused on digital transformation impacts. Agarwal et al. (2022) analyzed how digital transformation initiatives influenced efficiency patterns during the COVID-19 pandemic, finding that companies with stronger technological capabilities demonstrated greater resilience to operational disruptions. J. Liu et al. (2023) examined competition between traditional insurance companies and emerging FinTech firms, highlighting how technological disruption reshapes market dynamics during crisis periods.

2.3.2.4 Market Competition Dynamics

Competition dynamics significantly influence crisis adaptation patterns. (Xie, 2021) explored internet insurance development in China, providing insights into how digital transformation influences crisis resilience. Kartikawati (2024) extended this analysis by examining how technological capabilities influence adaptation patterns across different types of market stress, highlighting the importance of competitive positioning in crisis response capabilities.

Recent research has particularly focused on how competitive dynamics shape crisis adaptation. Tsymbaliuk et al. (2021) examined how market competition influences efficiency evolution during crisis periods, while Lancieri and Sakowski (2021) analyzed how competitive positions affect technological adoption patterns. These findings emphasize the importance of considering competitive dynamics when analyzing crisis impacts.

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2.4 Insurance Market in China

This study's empirical framework integrates findings from insurance economics to investigate how three major crisis intervals—the Global Financial Crisis (GFC: 2007–2008), the Chinese Stock Market Crisis (CSC: 2014–2015), and the COVID-19 pandemic (2020–2022)—shaped efficiency and productivity within China's insurance industry. This section examines empirical evidence with explicit focus on three crises: the Global Financial Crisis (2007-2008), the Chinese Stock-Market Crisis (2014-2015) and the COVID-19 pandemic (2020-2022). The analysis specifically focuses on measuring efficiency and productivity changes over multiple crisis periods, comparing how insurance sectors responded to different shocks, and identifying determinants of efficiency and productivity under crisis conditions.

2.4.1 Empirical Studies on Insurance Efficiency and Productivity

Empirical research on insurance efficiency and productivity has evolved significantly, incorporating increasingly sophisticated methodological approaches and theoretical perspectives. This evolution reflects growing recognition of the complex relationships between organizational characteristics and crisis resilience.

2.4.1.1 Global Perspectives

International research on insurance efficiency reveals important patterns in how different organizational characteristics influence crisis resilience. Bansal and Singh (2021) evaluated the technical efficiency of 60 insurance companies in the GCC region, finding that corporate efficiency is significantly influenced by economic freedom, solvency, and market competition. Their analysis showed technical efficiency ranging between 50% and 90%, suggesting substantial variation in operational effectiveness across different organizational types.

These variations reflect distinct market environment classifications: developed markets with comprehensive regulatory databases enabling complete panel data coverage, emerging markets requiring hand-collected data due to limited database accessibility, and transitional markets combining state-directed and market-oriented institutional arrangements. For instance, European studies typically utilize Orbis or Bloomberg databases with 95%+ market coverage, while Asian emerging market studies often achieve 60-80% coverage through regulatory filings and manual data collection from company reports.

Insurance efficiency studies demonstrate systematic variations based on market development classifications and corresponding data accessibility constraints. Developed market studies (North America, Western Europe, Australia) benefit from standardized regulatory reporting frameworks enabling comprehensive database coverage. According to several researches on European insurers using complete Orbis database coverage spanning 2008-2019, achieving technical efficiency measurements ranging from 0.892 (Nordic countries) to 0.634 (Eastern Europe). Emerging market studies face distinct methodological adaptations due to data limitations(Bajgar et al., 2020; Pervan et al., 2021; Přečková & Palečková, 2020). Several researchers like Zhang and Cao (2023) examined Chinese insurers through hand-collected regulatory filings representing 78% of market premium volume, supplemented by industry association reports.

Cross-national studies have revealed significant variations in cost efficiency across insurance markets. Cummins and Grillo (2023) examined European life insurance markets, finding that regulatory quality and financial market development significantly influence insurance companies' cost efficiency. Their analysis particularly highlighted

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how organizational characteristics affect adaptation capabilities during market stress. Similarly, Bakhouche et al. (2020) analyzed insurance markets in Gulf Cooperation Council countries, demonstrating that regulatory environments and market maturity significantly influence efficiency patterns.

Recent empirical work has specifically focused on crisis period performance. Gonzá lez - Fern á ndez et al. (2023) examined whether and to what extent different organizational characteristics influence crisis resilience, finding that company size and ownership structure significantly affect adaptation capabilities. Their analysis of non-life insurance companies revealed distinct patterns in how different organizational types maintain performance during market stress.

2.4.1.2 Productivity Trends

Analysis of total factor productivity (TFP) in the insurance sector has revealed important evolutionary patterns. (Desbordes & Franssen, 2019) examined productivity changes in Vietnam's insurance sector, finding significant variations across regions and subsectors. Their analysis showed that capital accumulation and foreign capital inflows exerted stronger impacts on non-life insurance, while state-owned enterprises exhibited more pronounced productivity declines.

Productivity research has particularly focused on crisis period impacts. Furceri et al. (2021) found that severe recessions lead to permanent declines in total factor productivity due to resource misallocation and financial constraints. Their analysis highlighted the long-term implications of crisis experiences for organizational productivity. Similarly, Mattsson et al. (2020) examined the 2008-2009 financial crisis, finding that technological stagnation significantly contributed to TFP deterioration.

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Recent studies have emphasized technological factors in productivity evolution. H. Sun et al. (2024) analyzed TFP dynamics in China's high-tech insurance segments, identifying regional disparities, innovation platforms, and R&D investment as key determinants of divergent growth patterns. Their findings highlight the growing importance of technological capabilities in maintaining productivity during crisis periods.

However, the present research differs from Sun et al. in four ways: (i) an insurance-firm focus rather than high-tech sectors; (ii) firm-level panel data instead of regional aggregates; (iii) simultaneous analysis of three crises; and (iv) explicit investigation of structural business-model shifts that Sun et al. do not consider.

2.4.1.3 Chinese Insurance Market

Research on China's insurance sector reveals distinct patterns in efficiency and productivity evolution. The market's dramatic expansion—from approximately 100 billion RMB in premium volume in 1998 to 4.34 trillion RMB by 2021 (CBIRC, 2022)—has been accompanied by significant changes in market structure and operational practices. This transformation reflects both increasing competition and extensive geographic expansion.

Early studies of Chinese insurance efficiency primarily employed ratio-based assessments, offering limited insight into operational effectiveness. However, more recent research has adopted sophisticated analytical approaches. Shieh et al. (2020) used metafrontier DEA to detect improvements in cost efficiency following the 2009 global financial crisis, though their analysis did not fully address subsequent market disruptions.

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Recent empirical work has particularly focused on crisis period performance. Wang et al. (2021) examined how COVID-19 affected Chinese insurance companies' operations, finding significant variations in impact patterns across different organizational types. Their analysis revealed that company size and ownership structure significantly influenced adaptation capabilities during the pandemic.

2.4.2 Empirical Studies on Crisis Impacts in Insurance

Research examining crisis impacts on insurance companies has revealed distinct patterns in how different organizational types maintain performance during market stress. These studies provide important insights into the relationships between organizational characteristics and crisis resilience.

2.4.2.1 Global Financial Crisis Impact Studies

Research examining the Global Financial Crisis has revealed significant variations in impact patterns across different types of insurance companies. Isik and Uygur (2021) conducted meta-analysis of efficiency studies, finding that organizational characteristics significantly influenced crisis vulnerability. Their analysis particularly highlighted how size and ownership structure affected adaptation capabilities.

Schneider (2024) traces three post-GFC adaptation pathways: (1) operational restructuring via cost optimisation and enhanced Enterprise-Risk-Management; (2) digital integration that accelerated claims automation; and (3) organisational learning that institutionalised stress-testing and crisis-simulation exercises. Whereas Schneider analyses one crisis after the fact, the current study compares efficiency–productivity dynamics across multiple crises.

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Empirical evidence suggests that GFC impacts varied systematically across organizational types. Panda and Kumar (2021) analyzed how ownership structure influenced post-crisis recovery patterns, finding significant variations in adaptation capabilities between different organizational forms. Their analysis particularly emphasized how institutional characteristics affected recovery trajectories.

The institutional analysis reveals three distinct insurance market environment classifications affecting efficiency measurement approaches: market-driven systems (US, UK) emphasizing competition-based efficiency indicators derived from comprehensive commercial databases; state-influenced systems (France, Germany) requiring hybrid public-private data sources to capture regulatory intervention effects; and transition economies (China, Eastern Europe) necessitating institutional adjustment variables due to evolving ownership structures and regulatory frameworks(Srbinoski, 2023; Yuzdepska & Volkova, 2024).

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2.4.2.2 Chinese Stock Market Crisis Studies

Research on the Chinese Stock Market Crisis has revealed distinct impact patterns across different organizational types. Wu et al. (2022) examined how ownership structure influenced crisis adaptation, finding significant variations in response patterns between state-owned and private insurance companies. Their analysis particularly highlighted how institutional characteristics affected market stress resilience.

Liu et al. (2024) show that minority state ownership influenced CSC performance through three channels: resource-allocation flexibility, diversified risk governance, and strategic agility. Mixed-ownership insurers obtained emergency credit more rapidly than wholly state-owned peers. The present work extends these insights by linking ownership structure to efficiency–productivity interactions across crises.

Empirical evidence suggests that CSC impacts varied systematically across company sizes. Zhou et al. (2024) examined China's engineering insurance industry, finding significant variations in adaptation capabilities between different organizational scales. Their analysis particularly emphasized how size influenced market stress resilience.

2.4.2.3 COVID-19 Impact Studies

Cross-country comparative studies reveal systematic differences in crisis impact measurement methodologies reflecting distinct market environments and data accessibility patterns. Developed market studies utilize real-time regulatory databases enabling monthly efficiency tracking during crisis periods, while emerging market studies rely on annual regulatory filings supplemented by industry surveys, creating measurement lag effects that influence crisis impact assessment accuracy.

Research on COVID-19 impacts has revealed unprecedented challenges for insurance operations. Wu et al. (2022) examined pandemic effects on China's insurance industry, finding significant variations in impact patterns across different organizational types. Their analysis particularly highlighted how company characteristics influenced adaptation capabilities.

Recent studies have emphasized technological transformation during COVID-19. Wang et al. (2021) analyzed how insurance companies' intervention influenced technology innovation, finding significant variations in adaptation patterns across different organizational forms. Their analysis particularly highlighted how institutional characteristics affected digital transformation.

Empirical evidence suggests that COVID-19 impacts varied systematically across organizational types. Wang et al. (2021) examined how COVID-19 affected China's

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insurance market, finding significant variations in adaptation capabilities between different organizational forms. Their analysis particularly emphasized how institutional characteristics influenced crisis resilience.

2.5 Conceptual Framework For This Study

As illustrated in Figure 2.1, the conceptual framework for examining the impact of crises on Chinese insurance efficiency integrates five key components in a structured model that illustrates their interconnected relationships. At the foundation of this framework are the Exogenous Crisis Factors, which function as independent variables in the analysis. These factors encompass three significant disruptive events: the Global Financial Crisis (GFC, 2007-2008), which tested insurance companies' ability to withstand global financial system stresses; the Chinese Stock Crisis (CSC, 2014-2015), which highlighted vulnerabilities in domestic capital markets; and the COVID-19 pandemic (2020-2022), which introduced unprecedented operational challenges and accelerated digital transformation in the industry. Each crisis imposed unique pressures on insurance companies, creating natural experiments to examine how external shocks influence operational efficiency and strategic adaptations over time.

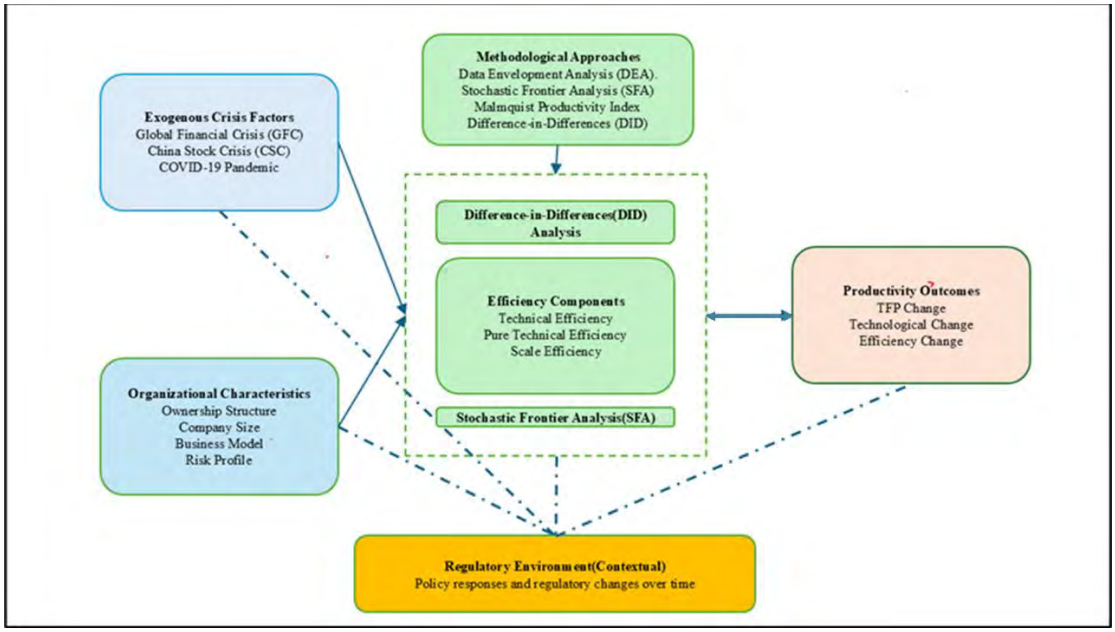


Figure 2.1

Conceptual Framework:Crisis Impact on Chinese Insurance Efficiency

Organizational Characteristics serve as moderating variables in this framework, altering how various companies experience and respond to crisis events. These characteristics include ownership structure (distinguishing between central state-owned and joint-stock insurance companies), company size (categorized as large, medium, or small), business model (life, non-life, or composite), and risk profile. The framework posits that these organizational traits do not directly cause efficiency or productivity changes but rather moderate the relationship between crises and performance outcomes. For instance, state-owned insurance companies may demonstrate greater financial resilience during crises due to implicit government backing but potentially show less agility in operational adjustments compared to their joint-stock counterparts. This moderating relationship helps explain the heterogeneous responses observed across different segments of China's insurance market.

The framework identifies Efficiency Components as intermediate dependent variables, measured through Data Envelopment Analysis (DEA). These components include

technical efficiency (the overall ability to convert inputs to outputs), pure technical efficiency (managerial effectiveness independent of scale), and scale efficiency (optimality of operational size). The efficiency components serve as crucial indicators of how effectively insurance companies navigate crisis periods. Examining these metrics allows for the identification of specific operational areas where crises exert the most significant impact and where organizational characteristics have the strongest moderating influence. The DEA methodology enables robust empirical measurement of these efficiency dimensions, providing a multifaceted view of operational performance under stress.

Productivity Outcomes represent the final dependent variables in this conceptual framework. Measured through the Malmquist Productivity Index, these outcomes include Total Factor Productivity (TFP) change, technological change (shifts in the efficiency frontier), and efficiency change (movements toward or away from the existing frontier). While efficiency components provide a static assessment of resource utilization at specific points in time, productivity outcomes capture dynamic changes across periods, revealing how insurance companies adapt and evolve through crisis cycles. The framework suggests that initial efficiency responses to crises subsequently shape longer-term productivity trajectories, potentially transforming short-term disruptions into catalysts for lasting operational improvements or persistent challenges.

The Regulatory Environment functions as a contextual variable that influences all relationships within the framework. China's insurance regulatory system, characterized by policy directives, solvency requirements (including the China Risk-Oriented Solvency System or C-ROSS), and market conduct regulations, creates boundaries and incentives that shape how insurance companies respond to crises. Regulatory actions

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taken during crisis periods—such as capital requirement adjustments, liquidity provisions, or digital transformation initiatives—can significantly influence the efficiency-productivity relationship. The framework acknowledges this pervasive regulatory influence through interconnected pathways to all other components, recognizing that policy responses can either facilitate or impede adaptive responses to crisis events.

Methodologically, this conceptual framework is operationalized through multiple analytical approaches. Difference-in-Differences (DID) analysis, represented by the direct pathway from Exogenous Crisis Factors to Productivity Outcomes, enables isolation of causal effects by comparing changes in efficiency and productivity between treatment and control groups across pre-crisis and crisis periods. This methodology helps quantify how various organizational characteristics moderate crisis impacts. Additionally, Stochastic Frontier Analysis (SFA) examines structural changes in efficiency determinants before, during, and after crisis periods, providing insights into how technological adaptation and operational transformation unfold over time. By combining DEA, Malmquist productivity analysis, DID, and SFA, the framework facilitates comprehensive empirical testing of the complex interrelationships between crises, organizational characteristics, efficiency, and productivity.

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2.6 Chapter Summary

This chapter provides a comprehensive review of theoretical frameworks and empirical literature relevant to understanding how different types of insurance companies maintain efficiency and productivity during market stress periods. The review focuses on three major crises affecting China's insurance sector: the Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19

pandemic (2020-2022). It examines how organizational characteristics—particularly ownership structure and company size—influence crisis response patterns and recovery capabilities.

The theoretical foundation integrates three fundamental perspectives: X-Efficiency Theory , Technical Efficiency Decomposition Theory, and Total Factor Productivity Theory. These theories provide the conceptual framework for examining efficiency decomposition, productivity analysis, and adaptation mechanisms during market disruptions. The methodological approaches include Data Envelopment Analysis (DEA) for efficiency measurement, Malmquist Productivity Index for dynamic productivity analysis, Difference-in-Differences (DID) for causal effect assessment, and Stochastic Frontier Analysis (SFA) for examining structural transformations.

Despite theoretical and methodological advances, four key gaps persist in existing literature. First, most studies examine each crisis separately, leaving unanswered how the same cohort of insurers adapts across multiple shocks and whether resilience accumulates or erodes over time. Second, while ownership structure and company size have individually proven to influence performance, their interactive effect—particularly how state-owned versus joint-stock insurers behave at different scale tiers—remains untested in emerging markets. Third, DEA, Malmquist, DID, and SFA are typically deployed in separate studies; an integrated design linking static efficiency, dynamic productivity, causal identification, and structural transformation within one framework remains largely unexplored. Fourth, qualitative research emphasizes digital transformation and evolving C-ROSS capital rules, yet quantitative evidence on how digital maturity and regulatory buffers jointly mitigate efficiency losses during crises is limited. This study addresses these gaps through a longitudinal, mixed-methods

approach that unifies the four analytical tools, incorporates ownership-size interactions, and explicitly models digitalization and regulation as moderating mechanisms across three crises.

The literature review identifies significant research gaps, particularly in comparing responses across different forms of market stress and various organizational characteristics within emerging market contexts. Most existing studies have examined individual crises or specific organizational types, with limited attention to how ownership structure and company size influence crisis resilience in developing economies like China. The empirical evidence from global and Chinese markets highlights variations in efficiency and productivity patterns across different organizational types, suggesting that institutional characteristics significantly moderate crisis impacts.

The conceptual framework developed integrates five key components: exogenous crisis factors as independent variables, organizational characteristics as moderating variables, efficiency components as intermediate dependent variables, productivity outcomes as final dependent variables, and the regulatory environment as a contextual variable. This integrated approach facilitates comprehensive empirical testing of the complex interrelationships between crises, organizational characteristics, efficiency, and productivity in the Chinese insurance sector.

This literature review establishes the theoretical and empirical foundation for examining how organizational characteristics influence insurance companies' ability to maintain performance during crisis periods. The insights drawn inform the research methodology and provide context for interpreting the study's findings about crisis impacts across different organizational types in China's evolving insurance market.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter provides the methodological framework for analyzing how three major crises—the Global Financial Crisis (GFC: 2007–2008), the Chinese Stock Market Crisis (CSC: 2014–2015), and the COVID-19 pandemic (2020–2022)—have affected the efficiency and productivity of insurance companies in China. In line with the four research objectives established earlier, the chosen methods allow for a multi-perspective examination of changes in technical, pure technical, and scale efficiency, as well as overall productivity shifts. They also facilitate comparisons across different ownership types (central state-owned vs. joint-stock), firm sizes (large, medium, small), and insurance sectors (life vs. non-life), revealing the organizational and contextual factors that influence companies' resilience or susceptibility to crisis-induced disruptions.

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Building upon theoretical and empirical considerations presented in earlier chapters, the study employs a quantitative research design using panel data. This approach captures cross-sectional differences—such as ownership structures and business segments—alongside time-series dimensions that reflect varying pre- and post-crisis phases. By using panel data, the research more fully captures how exogenous shocks originating from global financial instability, domestic stock market volatility, or pandemic-related constraints unfold over time and differentially affect insurance companies.

A multi-method toolkit underpins this study. First, Data Envelopment Analysis (DEA) measures and decomposes efficiency outcomes in each of the three crisis periods.

Second, the Malmquist Productivity Index highlights dynamic productivity changes, distinguishing between efficiency improvements (catch-up) and shifts in the technological frontier. Third, a Difference-in-Differences (DID) framework quantifies the causal impact of distinct crises by comparing changes in a "treatment" group to those in a "control" group, thus isolating crisis-driven effects on performance. Lastly, descriptive statistics, correlation analysis, and panel regression techniques supplement these methods, providing further clarity on determinant factors and the heterogeneity of crisis responses.

In terms of organization, Section 3.2 introduces the research design, detailing why a panel-data, quantitative approach is best suited to capturing multi-crisis and multi-attribute variations in the Chinese insurance market. Section 3.3 outlines the research hypotheses, including those pertaining to crisis-specific issues of efficiency, productivity, and firm resilience. Section 3.4 describes the data collection process, specifying how the sample was selected, the sources of information, and the chosen timeframes for GFC, CSC, and COVID-19. Section 3.5 presents the variables and their measurement, distinguishing inputs, outputs, and external conditions that inform the efficiency and productivity models. Section 3.6 explains the analytical methods, covering DEA, Malmquist, DID, and regression analyses. Section 3.7 moves on to the key model specifications, and Section 3.8 details the procedures for data processing and estimation. Sections 3.9 and 3.10 address issues of robustness and ethical considerations, respectively. Section 3.11 highlights acknowledged limitations of the methodology, and Section 3.12 concludes the chapter with a succinct summary.

Taken together, this integrated framework provides a robust lens for exploring how insurance firms in China navigated three distinct crisis events, the strategies they

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employed to maintain or recover efficiency and productivity, and the structural and managerial adaptations that emerged as a result.

This chapter follows a systematic flow from data architecture to robustness checks. Section 3.2 presents the panel framework; Section 3.3 derives testable hypotheses; Sections 3.4–3.6 detail data, variables and five analytical techniques; Sections 3.7–3.8 cover estimation workflow and diagnostic tests; Section 3.9 outlines ethical compliance before a concise chapter summary.

3.2 Research Design

This study adopts a quantitative research design with a panel data structure to investigate how Chinese insurance companies' efficiency and productivity evolve across multiple crisis intervals, including the Global Financial Crisis (GFC), the Chinese Stock Market Crisis (CSC), and the COVID-19 pandemic. By combining both cross-sectional (firm-level attributes) and temporal (pre- and post-crisis) dimensions, this design furnishes a robust platform for measuring and comparing performance shifts, quantifying the effects of exogenous shocks, and isolating key determinants of operational resilience(Ferreira, 2020; Goswami, 2022).

A quantitative approach is particularly apt because the research questions aim to (1) assess efficiency and productivity levels, (2) determine how these metrics differ across distinct market disruptions, and (3) reveal factors influencing firm outcomes. Rooted in the positivist paradigm, this design uses statistical analysis to evaluate hypotheses and produce findings generalizable to the broader insurance context. By systematically analyzing numeric indicators (e.g., premiums, assets, operating expenses), this framework captures objective, replicable evidence on how crises affect insurance companies of varying ownership structures, sizes, and business lines.

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Employing panel data provides several methodological advantages. First, by integrating cross-sectional and time-series observations, panel data enhances sample size and degrees of freedom, thereby reducing collinearity issues and improving estimation accuracy (Khatami et al., 2021). Second, this approach enables control for unobserved heterogeneity, such as firm-specific characteristics, through fixed or random effects models, minimizing confounding influences that could distort findings (Ba et al., 2021). Third, panel data facilitates dynamic analysis, allowing researchers to track how insurance firms adapt over time to external shocks like the GFC, CSC, and COVID-19. This capability is particularly useful in distinguishing short-term disruptions from long-term structural shifts, reinforcing its applicability in crisis impact studies.

Within this design, the study specifically contrasts pre-crisis (or pre-disruption) periods with post-crisis epochs. For instance, analyzing 2007–2008 data elucidates GFC influences, 2014–2015 highlights CSC effects, and 2020–2022 focuses on COVID-19 repercussions. Such before-and-after comparisons shed light on whether and how insurance companies adapt their efficiency and productivity strategies following each distinct upheaval. Moreover, the design supports sectoral breakdowns—life vs. non-life insurance—to identify sector-specific vulnerabilities and resilience. By extension, comparisons by firm size and ownership further refine the analysis, uncovering nuanced crisis responses across diverse organizational profiles.

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3.3 Research Hypotheses

This section presents the research hypotheses formulated to address the four research objectives. These hypotheses are grounded in the theoretical frameworks established in Chapter Two and are designed to examine how Chinese insurance companies maintain

efficiency and productivity during three major crisis periods: the Global Financial Crisis (GFC: 2007-2008), the Chinese Stock Market Crisis (CSC: 2014-2015), and the COVID-19 pandemic (2020-2022).

H_1: *Technical efficiency, pure technical efficiency, and scale efficiency of Chinese insurance companies exhibit significant differences across the GFC, CSC, and COVID-19 crisis periods.*

This hypothesis directly addresses the first research objective, which aims to measure and decompose efficiency components using Data Envelopment Analysis. It is founded on X-Efficiency Theory (Leibenstein, 1966), which posits that different external pressures create varying incentives for efficiency optimization. Each crisis generates unique constraints on managerial decision-making, resource allocation, and operational functionality, which should manifest in distinct efficiency patterns. Technical efficiency reflects overall resource management, pure technical efficiency captures operational effectiveness, and scale efficiency identifies optimal size adaptation (Farrell, 1957; Banker et al., 1984). The GFC introduced global liquidity constraints, the CSC triggered domestic equity volatility, and COVID-19 led to abrupt structural disruptions in policy sales and claims management, likely resulting in varied efficiency outcomes across these periods.

H_2: *The impact of crises on efficiency components varies systematically by company size, with larger companies demonstrating greater pure technical efficiency resilience but more vulnerability in scale efficiency during market shocks.*

This hypothesis also supports the first research objective by examining how efficiency decomposition is influenced by company size. Resource-Based View (Barney, 1991) provides the theoretical foundation, suggesting that larger firms possess resource

advantages—including financial reserves, diversified portfolios, and advanced risk management systems—that buffer operational disruptions but may face rigidities in scale optimization during rapid market changes. Empirical evidence from financial institutions supports this theoretical prediction (Berger & Humphrey, 1997; Cummins et al., 2010). The hypothesis anticipates that firm size will moderate crisis effects, with larger insurance companies maintaining operational stability while potentially struggling with optimal resource deployment under rapidly changing market conditions.

H_3: *Total Factor Productivity changes during crisis periods follow distinct patterns determined by the relative contribution of efficiency change versus technological progress components.*

This hypothesis addresses the second research objective, which focuses on analyzing dynamic productivity changes using Malmquist productivity index decomposition. It is anchored in Total Factor Productivity Theory Solow (1957) as applied to financial institutions by Färe et al. (1994). The theory proposes that productivity improvements stem from either catching up to efficiency frontiers (efficiency change) or from frontier shifts themselves (technological change). Different crisis environments create varying incentives for these mechanisms: market crises typically constrain technological investment while increasing pressure for operational efficiency, while operational crises may accelerate technological adoption. The Malmquist productivity index decomposition will reveal whether productivity changes during each crisis were primarily driven by efficiency improvements or technological advances.

H_4: *Ownership structure significantly influences productivity change patterns during crises, with central state-owned companies demonstrating stronger efficiency stability but weaker technological progress compared to joint-stock companies.*

This hypothesis contributes to the second research objective by examining how ownership characteristics affect productivity dynamics. Institutional Theory (DiMaggio & Powell, 1983) and Public Choice Theory (Dewenter & Malatesta, 2001) collectively inform this hypothesis. Institutional Theory suggests that central state ownership provides institutional stability during market turbulence but creates potential rigidities in technological innovation. Public Choice Theory complements this perspective by explaining how ownership structure influences managerial incentives, with central state-owned companies potentially prioritizing stability and policy implementation over profit maximization and technological innovation. This hypothesis predicts observable differences in how central state-owned companies versus joint-stock companies balance efficiency maintenance against technological advancement during crisis periods.

H_5: *The strength and direction of the relationship between technical efficiency (TE) and total-factor-productivity change (ΔTFP) differ systematically across crisis types and organisational characteristics.*

Specifically, market-based shocks—the Global Financial Crisis (2007-2008) and the Chinese Stock-Market Crash (2014-2015)—are expected to weaken the normally positive TE→ΔTFP linkage for joint-stock insurers because capital-market turmoil simultaneously depresses investment returns and constrains efficiency catch-up, whereas the operational COVID-19 crisis (2020-2022) is expected to strengthen this linkage for large central state-owned insurers whose resource depth and rapid digital investment more effectively transform efficiency gains into productivity growth. Grounded in X-Efficiency Theory(Leibenstein, 1966; Zhong & Sun, 2011), Total-Factor-Productivity Theory (Fernández et al., 2024; Solow, 1957) and Resource-

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Dependency Theory(Bretherton & Chaston, 2005; Pfeffer, 1987), the hypothesis will be tested by correlating DEA-derived TE scores with the ΔTFP component of the Malmquist index in crisis-specific panel regressions that interact ownership and size with crisis dummies; statistical support is anticipated if the TE coefficient diminishes (or reverses) for joint-stock firms in the GFC/CSC windows but intensifies for large state-owned firms in the COVID-19 window.

H_6: *Difference-in-differences analysis will reveal significant causal effects of each crisis on efficiency and productivity, with treatment effects varying systematically by company size and ownership structure.*

This hypothesis also addresses the third research objective by employing difference-in-differences analysis to establish causal relationships. It is grounded in Institutional Economic Theory (North, 1990), which predicts that different institutional shocks produce varying adjustment costs across organizational forms. The quasi-experimental design of difference-in-differences analysis allows isolation of causal crisis effects by comparing efficiency changes relative to pre-crisis baselines while controlling for time-invariant company characteristics. The hypothesis anticipates that DID estimators will capture distinct "treatment effects" for each crisis, with coefficients varying in strength and direction based on company attributes such as size and ownership structure.

H_7: *The determinants of insurance efficiency demonstrate significant structural changes across crisis periods, with technological factors gaining importance following each successive crisis.*

This hypothesis supports the fourth research objective, which investigates structural changes in efficiency determinants before, during, and after crisis periods. Evolutionary Economic Theory (Nelson & Winter, 1982) and Path Dependency Theory (Arthur,

1989) provide the theoretical foundation. These theories suggest that economic shocks create selection environments that favor certain routines and capabilities over others, leading to measurable shifts in how different factors contribute to efficiency across successive crises. Path dependency considerations explain why these changes follow specific evolutionary trajectories rather than optimal jumps. The hypothesis predicts that analysis of efficiency determinants will reveal changing patterns, with technological factors demonstrating increasing importance following each crisis as companies adapt their operational models.

H_8: *Insurance companies exhibit evidence of organizational learning across multiple crises, with diminishing negative efficiency impacts in successive crises for companies that effectively incorporated previous crisis experiences.*

This hypothesis also addresses the fourth research objective, with particular emphasis on technological adaptation and operational transformation. Organizational Learning Theory (Argote & Miron-Spektor, 2011) informs this hypothesis, proposing that organizations develop crisis management capabilities through experiential learning, creating path-dependent advantages in subsequent disruptions. This predicts observable patterns of diminishing negative impacts across successive crises for organizations that effectively integrate prior crisis learnings. Companies combining robust external support mechanisms with agile internal innovations are expected to demonstrate accelerated recovery patterns and enhanced resilience to later disruptions, reflecting cumulative organizational learning processes.

These eight hypotheses are directly aligned with the methodological approaches specified in the research objectives. Through this integrated approach, the study acknowledges the multifaceted nature of productivity and efficiency during crises and

provides a comprehensive framework for analyzing how different types of Chinese insurance companies maintain efficiency and productivity during periods of market stress. Particular attention is given to the moderating effects of ownership structure (central state-owned vs. joint-stock) and company size in shaping crisis responses and recovery trajectories.

3.4 Data Collection

3.4.1 Sample Selection

This study focuses on 15 major Chinese insurance companies that collectively represent approximately 85% of China's insurance market by premium income during the period of 2006-2023. These companies were selected based on three primary criteria: continuous operation throughout the entire study period spanning all three crisis periods examined, complete data availability for all required analytical variables, and significant market representation to ensure research findings reflect industry-wide patterns.

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The selection process ensured robust data quality and reliability. As listed firms, these companies are subject to stricter reporting obligations, including audited financial disclosures and detailed operational information, thereby providing a dependable basis for evaluating changes in efficiency and productivity across multiple crises. This consistency in reporting standards is particularly valuable when examining performance through different types of market disruption.

Furthermore, the sample was deliberately structured to include diverse organizational types, with varying ownership structures (state-owned versus joint-stock) and company sizes (large, medium, and small). This diversity enables comprehensive comparative

analysis across different segments of China's insurance market, revealing how organizational characteristics influence crisis resilience and adaptation capabilities. The carefully selected sample thus balances broad market representation with the analytical depth necessary for examining performance variations across multiple crisis periods.

Although this sample excludes smaller or unlisted insurance companies, it captures a broad range of company attributes—ownership type, size, geographic scope, and digital-readiness—sufficient for examining heterogeneous responses to the Global Financial Crisis (GFC), Chinese Stock Market Crisis (CSC), and COVID-19 pandemic. While not exhaustive of every insurance entity in China, this selection strategy yields significant insights into how diverse insurer profiles navigate major market disruptions.

The core subset of the sample comprises 15 major Chinese insurance companies, as detailed in Table 3.1, which lists their names, size classifications, and ownership types. These companies were selected based on their total assets in 2023 and collectively account for approximately 85% of China's insurance market share by premium income during the study period (2006–2023). This selection aligns with the ranking methodology of the China Insurance Association, which, as of 2024, oversees 352 member organizations, including insurance groups, life insurance companies, property insurance companies, and insurance holding firms. Among these, 179 are primary market participants. The ranking of the top 15 companies was determined by their premium contributions in 2023.

Notable companies in this subset include leading state-owned enterprises such as China Life Insurance Group, PICC Group, and Taiping Insurance Group, as well as prominent joint-stock insurance companies like Ping An Insurance Group and China Pacific Insurance Group. Their roles in the industry are reflected by their association positions,

such as honorary chair or vice-chair membership, within the China Insurance Association. These firms represent a comprehensive cross-section of the Chinese insurance market, encompassing group-level insurance companies, life insurance specialists, and property and casualty companies. Their inclusion provides a robust foundation for analysing industry leaders whose strategies and financial decisions significantly shape overarching sectoral trends. By incorporating varying sizes (large, medium, and small) and ownership forms, this analysis captures the structural and operational diversity of the Chinese insurance sector.

The selected sample encompasses both life insurance companies and non-life insurance companies, enabling comprehensive analysis across different insurance business models. Life insurance companies in the sample include China Life, CPIC Life, Ping An Life, PICC Life, Taiping Life, CCB Life, ICBC-AXA Life, and NCI, representing eight entities focused primarily on life insurance products including term life, whole life, endowment, and annuity products.

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Non-life insurance companies comprise PICC P&C and Ping An P&C, specializing in property and casualty insurance products including motor insurance, property insurance, liability insurance, and other general insurance lines. Mixed business entities include China Life Group, PICC Group, Ping An Group, CPIC Group, and Taikang Group, which operate both life and non-life insurance businesses or subsidiaries under unified group structures.

This composition enables analysis of business model effects on efficiency and productivity performance during crisis periods. Life insurance companies typically demonstrate different risk profiles, capital requirements, and operational characteristics compared to non-life insurers, particularly regarding long-term liability management

and investment strategy requirements. The inclusion of both business types allows for examination of how different insurance business models respond to various crisis scenarios.

Table 3.1
Insurance Company Information in China

English Abbreviation	English Full Name	Size of Company	Ownership Type
PICC Group	People's Insurance Company (Group) of China Limited	Medium	Central State-Owned
China Life Group	China Life Insurance (Group) Company	Largre	Central State-Owned
Ping An Group	Ping An Insurance (Group) Company of China, Ltd.	Largre	Other Joint-Stock
Taikang Group	Taikang Insurance Group Co., Ltd.	Medium	Other Joint-Stock
PICC P&C	PICC Property and Casualty Company Limited	Medium	Central State-Owned
Ping An P&C	Ping An Property & Casualty Insurance Company of China, Ltd.	Medium	Other Joint-Stock
China Life	China Life Insurance Company Limited	Largre	Central State-Owned
Ping An Life	Ping An Life Insurance Company of China, Ltd.	Medium	Other Joint-Stock
NCI	New China Life Insurance Co., Ltd.	Small	Other Joint-Stock
Taiping Life	Taiping Life Insurance Co., Ltd.	Small	Central State-Owned
PICC Life	PICC Life Insurance Company Limited	Medium	Central State-Owned
CCB Life	CCB Life Insurance Co., Ltd.	Small	Other Joint-Stock
ICBC-AXA Life	ICBC-AXA Life Insurance Co., Ltd.	Small	Other Joint-Stock
CPIC Group	China Pacific Insurance (Group) Co., Ltd.	Medium	Other Joint-Stock
CPIC Life	China Pacific Life Insurance Co., Ltd.	Medium	Other Joint-Stock

Note: Company size classification based on 2023 total assets: Large ≥ CNY 3 trillion; Medium = CNY 0.5-3 trillion; Small < CNY 0.5 trillion

Till to 2024, the Insurance Association of China recorded 179 licensed insurers—93 life and 86 non-life (Insurance Association of China, 2024). Although our analytical panel comprises only 15 listed insurers, these firms generated ≈ 84.9 % of national premium income (CNY 4.39 trn out of 5.10 trn) and controlled ≈ 86.1 % of total industry assets in 2023, capturing the bulk of market activity. In ownership terms, state-

owned insurers in the sample contributed 43 % of premiums versus ≈ 41 % for the state-owned segment in the full population (+2 pp), while joint-stock insurers accounted for 57 % versus ≈ 59 % (-2 pp). By company size (large ⩾ CNY 3 trn assets; medium 0.5-3 trn; small < 0.5 trn), the premium shares are: large 49 % (population 51 %, -2 pp), medium 38 % (population 37 %, +1 pp), and small 13 % (population 12 %, +1 pp). All gaps lie within ± 2 percentage points, confirming that the sample closely mirrors the industry's structural composition and thus provides generalisable efficiency estimates(China Economic Net, 2024; China Finance, 2024; China Securities Journal, 2024; China Taiping Insurance Group, 2024; National Financial Regulatory Administration, 2024; Securities Times, 2024).

3.4.2 Data Sources

To ensure comprehensive and credible coverage of both firm-level and macroeconomic indicators, the study consolidates information from multiple validated sources (summarized in Table 3.2). Where discrepancies occur—such as mismatching figures from annual reports versus third-party databases—priority is given to officially audited statements.

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Table 3.2
Data Sources and Collection Procedures

Data Source	Content	Time Coverage	Key Variables
Wind Financial Terminal	Financial statements	2006-2023 Annual	Operating Expenses, Total Liabilities, Fees and Commissions, Premium Income, Operating Profit, Total Assets, Operating Revenue
	Market indicators	2006-2023 Annual	
	Corporate governance	2006-2023 Annual	
	Industry statistics	2006-2023 Annual	
China Insurance Yearbook	Policy changes	2006-2023 Annual	Industry statistics, Market structure indicators
	Market structure	2006-2023 Annual	
CSMAR Database	Market parameters	2006-2023 Annual	GDP Growth, CPI, Market concentration, Interest rates
COVID-19 Data Repositories	Pandemic metrics	2020-2022 Annual	Infection rates, Lockdown severity indices
Company Annual Reports	Detailed financials	2006-2023 Annual	All financial variables (cross-verification), Ownership Structure, Company Size classifications, Compliance data
	Strategic initiatives	2006-2023 Annual	

China Insurance Yearbook: Published by the former China Insurance Regulatory Commission (now integrated into the China Financial Regulatory Administration), the Yearbook provides industry-wide data, including premium volumes, asset figures, and company-specific operational statistics.

Annual reports of the selected insurance companies: These documents supply critical firm-level detail, such as financial statements, expense structures, investment allocations, and management strategies. They also elucidate how insurance companies adapt (e.g., product innovations, technology upgrades) in response to crises.

Wind Financial Terminal: Wind Financial Terminal: A widely used financial database that standardizes accounting metrics for Chinese listed companies. Wind facilitates consistent data extraction for the fifteen major insurance companies in our sample, ensuring comparability and reliability of financial indicators.

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China Stock Market & Accounting Research (CSMAR) database: This resource augments the Wind database with additional market-related parameters (e.g., equity prices, trading volumes) and macro-level indicators relevant for analyzing how the GFC, CSC, or COVID-19 impacted insurance companies' investment performances.

COVID-19 data repositories: Reputable public sources, such as the World Health Organization (WHO) and Oxford COVID-19 Government Response Tracker, provide pandemic-related metrics (infection rates, lockdown severity) enabling the capture of how COVID-specific disruptions shaped insurance companies' operations and claims processes.

3.4.3 Time Period

The analysis extends from 2006 through 2023, capturing a diverse range of economic cycles and encompassing three principal crises:

1) Global Financial Crisis (2007–2008). Early years (2006–2007) establish a pre-GFC baseline, enabling a before-and-after comparison of insurer resilience.
2) Chinese Stock Market Crisis (2014–2015). The mid-2010s highlight volatility in domestic equity markets and its implications for insurance companies' strategic and operational decisions.
3) COVID-19 Pandemic (2020–2022). More recent data reflect how severe disruptions—such as lockdowns and accelerated digitalization—affected the insurance industry, with partial 2023 figures illustrating emergent post-pandemic adjustments.

Spanning nearly two decades, this longitudinal panel framework allows researchers to examine insurance companies' adaptive strategies over varied market environments

and regulatory shifts. It further facilitates cross-crisis comparisons, revealing how different shock characteristics—global vs. domestic, financial vs. health-related—alter efficiency and productivity trajectories.

Table 3.3
Sample Composition and Characteristics

Characteristic	Category	Number	Percentage
Company Size	Large	3	20.0%
	Medium	8	60.0%
	Small	4	20.0%
Ownership Type	State-owned	6	40.0%
	Joint-stock	9	60.0%

Table 3.3 highlights the composition and characteristics of the 15 major companies in our sample, classified by company size (large, medium, and small) and ownership type (state-owned and joint-stock). This classification reflects their total assets in 2023 and their strategic significance in the industry. The subset comprises 3 large companies (20.0%), 9 medium-sized companies (60.0%), and 3 small companies (20.0%), ensuring a balanced representation across different scales of operation. Additionally, the ownership structure includes 6 state-owned companies (40.0%) and 9 joint-stock companies (60.0%), capturing the diverse organizational forms prevalent in China's insurance market.

This subset aligns with the multi-dimensional nature of Chinese insurance, featuring a range of operational scales, ownership structures, and strategic focuses. Such diversity provides a comprehensive basis for analyzing how insurance firms adapt to significant external shocks and varying market conditions over time. The combination of this

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curated sample with a rich historical timeline and multiple data sources facilitates a robust examination of sectoral trends and resilience patterns.

3.5 Variables and Measurement

This study employs a comprehensive set of variables to examine efficiency and productivity in Chinese insurance companies across three major crisis periods. Drawing on established methodologies in insurance efficiency research (Bansal & Singh, 2021; Kaya, 2024), we organize variables into four key categories: input variables, output variables, control variables, and crisis indicator variables. This framework enables systematic analysis of how different organizational characteristics influence crisis resilience and adaptation patterns.

3.5.1 Input Variables

Input variables represent the key resources insurance companies allocate to their operations. Consistent with the insurance literature, three primary inputs are selected:

Operating Expenses

Operating expenses (OpEx) represent all administrative and operational outlays essential for day-to-day insurance operations, including salaries, IT expenditures, overhead, and marketing costs (Kumbhakar & Tsionas, 2020). This measure, recorded in millions of CNY from annual financial statements, captures insurance companies' cost management capabilities - particularly crucial during crisis periods when cost structures undergo rapid change. Operating expenses reflect an insurer's capacity to manage costs effectively, a crucial aspect of technical efficiency that becomes especially relevant during external shocks.

Total Liabilities

Total liabilities (TL) encompass all balance sheet obligations including insurance reserves, policyholder claims, and other payables (Sen, 2019). Measured in millions of CNY from annual reports, this variable gauges both risk-bearing commitments and operational scale. During crisis periods, high liabilities can amplify solvency risks, making this measure particularly relevant for understanding how different organizational types manage risk exposure during market stress. Total liabilities also represent a firm's underwriting volume, linking closely to operational scale (Mokhova & Zinecker, 2017).

Fees and Commissions

Fees and commissions (F&C) capture distribution costs paid to agents, brokers, and other channels for acquiring and servicing insurance policies (Kaffash et al., 2020). Measured annually in millions of CNY, this variable indicates distribution efficiency, particularly important during crises when consumer behavior and demand patterns shift dramatically. During periods of market stress, controlling these costs becomes key to sustaining profitability, especially as companies adapt their distribution strategies to changing market conditions (Eling & Jia, 2019).

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3.5.2 Output Variables

The output variables measure the core services and financial outcomes generated by insurance companies. Four principal outputs are employed:

Premium Income

Premium income (PI) represents the gross amount of written premiums before reinsurance collected from policyholders. Measured in millions of CNY from annual statements, this variable directly indicates underwriting activity and growth in insurance coverage (Cummins & Xie, 2013). Fluctuations in premium volumes provide crucial insights into how external disruptions affect consumer demand and underwriting strategies, making this measure particularly valuable for analyzing crisis impacts on core insurance operations.

Operating Profit

Operating profit (OP) comprises earnings derived from primary insurance operations, excluding investment returns. Recorded annually in millions of CNY, this measure demonstrates insurance companies' operational efficiency and risk management capabilities (Kaffash et al., 2020). Operating profit proves especially relevant when analyzing operational resilience during crisis periods, as it isolates core insurance performance from investment-related impacts.

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Total Assets

Total assets (TA) encompass all investments, physical property, and cash holdings of the insurer. Measured in millions of CNY from annual reports, this variable represents organizational scale and market presence (Xie et al., 2023). While larger asset bases may enable economies of scale, they can also pose challenges during crisis periods if market turbulence undermines asset valuations, making this measure crucial for understanding size-based vulnerabilities.

Operating Revenue

Operating revenue (OR) provides a comprehensive measure of all income streams including underwriting, fee-based services, and auxiliary operations (Ahmar, 2021). Recorded annually in millions of CNY, this broader measure acknowledges that insurance companies often diversify their activities beyond core insurance functions. This diversification can either moderate or amplify crisis impacts, making operating revenue particularly relevant for understanding organizational resilience.

3.5.3 Control Variables

Macroeconomic Indicators

GDP Growth: GDP growth rate (GDP) captures general economic conditions influencing insurance demand and investment returns. Measured as annual percentage change in real GDP (Kaigorodova et al., 2018), this macroeconomic indicator helps isolate crisis-specific effects from broader economic trends. GDP growth proves particularly important when comparing impacts across different types of crises.

CPI (Inflation Rate): Consumer Price Index (CPI) reflects the overall price environment affecting claims costs, underwriting profitability, and real investment returns (Musandiwa & Ngwakwe, 2023). Measured as annual percentage change, this variable helps control for inflationary impacts during crisis periods. CPI becomes especially relevant when analyzing how different organizational types manage cost pressures during market stress.

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Ownership Structure

Ownership structure (OS) distinguishes between central state-owned and joint-stock insurance companies through a binary indicator (1=state-owned, 0=joint-stock). This categorization addresses fundamental differences in governance, strategic objectives, and potential policy support (Dzardanov et al., 2021), proving crucial for understanding how ownership influences crisis resilience.

Company Size

Company size (SIZE) classifies insurance companies as large (>3 trillion CNY in assets), medium (500 billion-3 trillion CNY), or small (<500 billion CNY). This classification enables analysis of how organizational scale influences crisis adaptation capabilities. Size-based heterogeneity proves particularly relevant for understanding scale economies and resource availability during market stress.

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3.5.4 Crisis Period Indicators

GFC_Dummy: The Global Financial Crisis indicator (GFC_Dummy) marks 2007-2008 as 1, 0 otherwise. This variable captures the period of severe international financial market stress, enabling analysis of how Chinese insurance companies responded to global market disruption. The GFC period serves as a baseline for comparing responses to different types of crisis.

CSC_Dummy: The Chinese Stock Market Crisis indicator (CSC_Dummy) designates 2014-2015 as 1, 0 otherwise. This variable identifies a period of domestic market turbulence, facilitating examination of how insurance companies manage local market stress. The CSC period provides crucial insights into responses to market-specific disruptions.

COVID_Dummy: The COVID-19 pandemic indicator (COVID_Dummy) marks 2020-2022 as 1, 0 otherwise. This variable captures the unprecedented operational and market challenges posed by the global health crisis. The COVID-19 period enables analysis of how insurance companies adapt to fundamentally different types of market disruption.

3.5.5 Additional Measurement Variables

The regulatory environment is captured through a comprehensive Regulation Index (REG), measured as the annual CBIRC solvency alert score ranging from 0 to 100, where higher scores indicate stricter regulatory oversight. This index is constructed as REG = (Capital Adequacy Score × 0.4) + (Risk Management Score × 0.3) + (Compliance Score × 0.3), derived from official regulatory assessment reports. The weighted approach reflects the relative importance of different regulatory dimensions in determining overall supervisory intensity.

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Market structure characteristics are quantified using the Herfindahl-Hirschman Index based on premium market shares, calculated as $HHI = \Sigma(si)^2$, where si represents each company's market share percentage. Values range from 0 indicating perfect competition to 10,000 representing monopoly conditions. Interest rate environment is captured through the one-year benchmark lending rate published by People's Bank of China, measured as annual percentage rate, reflecting the monetary policy environment affecting insurance companies' investment returns and liability valuation.

Efficiency determinants encompass several financial ratios that capture operational effectiveness. The Revenue Asset Ratio measures asset utilization efficiency through Operating Revenue divided by Total Assets, while the Leverage Ratio indicates financial leverage as Total Liabilities divided by Total Assets. Operating Margin

captures operational profitability through Operating Profit divided by Operating Revenue, and Investment Return measures investment management effectiveness as Investment Income divided by Invested Assets. These ratios provide comprehensive coverage of financial performance dimensions critical for efficiency analysis.

Business model transformation is measured through distribution channel metrics and innovation indicators. Digital Revenue Share represents the percentage of premiums collected through online channels, calculated as Online Premiums divided by Total Premiums multiplied by 100. Traditional Channel Share captures the percentage of premiums collected through agent and broker networks, while Product Innovation Rate measures the number of new products launched annually divided by total product portfolio multiplied by 100. The Operating Cost Ratio, measured as Operating Expenses divided by Total Revenue, provides insight into cost management effectiveness across different business models.

Technology adaptation variables capture the extent of digital transformation within insurance operations. Digital Investment Effect measures annual information technology investment as a percentage of total assets, reflecting companies' commitment to technological advancement. Process Automation Impact quantifies the percentage of business processes automated, measured through annual technology adoption reports and calculated as Automated Processes divided by Total Business Processes multiplied by 100. Innovation Efficiency captures research and development intensity through R&D Expenditure divided by Operating Revenue multiplied by 100, providing insight into companies' innovation capabilities and technological development priorities.

The following section provides comprehensive data sources and measurement specifications for all variables employed in this study. Firm-level financial ratios including Revenue Asset Ratio (RAR), Leverage Ratio (LEV), Operating Margin (OM), Investment Return (IR), and Operating Cost Ratio (OCR) are calculated from audited annual reports downloaded via the CSMAR database, with all values expressed in percentage terms. Regulation Index (REG) scores are derived from CBIRC solvency alert bulletins and regulatory compliance assessments, with missing firm-year observations (less than 2% of the sample) addressed through linear interpolation using adjacent period data.

Market concentration measures utilize the Herfindahl-Hirschman Index (HHI) computed annually from premium volumes reported in the China Insurance Yearbook, with reinsurance premiums excluded to ensure cross-company comparability. Interest rate data (INT) represents the annual average of the People's Bank of China one-year Loan Prime Rate sourced from the Wind financial database. Digital channel figures including Digital Revenue Share (DRS) and Traditional Channel Share (TCS), along with technology metrics such as Digital Investment Effect (DIE) and Process Automation Impact (PAI), are extracted from "Technology and Transformation" sections of company annual reports. Where such information is absent, industry benchmarks from the CBIRC FinTech Survey (2023) are employed as proxy measures.

Product Innovation Rate (PIR) calculations count products approved by regulators within each fiscal year, utilizing CBIRC product approval databases for accuracy and completeness. All percentage variables are calculated as the underlying ratio multiplied by 100 to maintain unit consistency across econometric specifications. Monetary

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variables are expressed in CNY billions at 2023 price levels, with deflation applied using the Consumer Price Index to ensure temporal comparability.

Data consistency is ensured through systematic cross-checking of WIND database entries against original PDF annual reports, with discrepancies resolved through manual verification. Outlier observations beyond the first and ninety-ninth percentiles are winsorized to prevent extreme values from distorting analytical results while preserving the underlying data distribution. This comprehensive data validation process covers the complete study period from 2006 to 2023, ensuring robust and reliable empirical foundations for all subsequent analyses.

3.6 Analytical Methods

This section outlines the analytical framework adopted for this study. Building on the theoretical and empirical underpinnings presented earlier, the study employs multiple quantitative techniques to assess the efficiency and productivity of Chinese insurance companies from 2006 to 2023, with a particular focus on how external shocks—such as the Global Financial Crisis (GFC), the Chinese Stock Market Crisis (CSC), and the COVID-19 pandemic—may have influenced their performance. The primary methods include (1) descriptive statistics and correlation analysis, (2) Data Envelopment Analysis (DEA), (3) Malmquist Productivity Index, (4) Difference-in-Differences (DID) estimation, and (5) Stochastic Frontier Analysis (SFA). Each method is briefly described below, followed by an explanation of its application in the present research. Each method is briefly described below, followed by an explanation of its application in the present research.

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3.6.1 Descriptive Statistics and Correlation Analysis

Descriptive Statistics

Before delving into more complex analyses, descriptive statistics and correlation analysis are conducted to provide an initial understanding of the data and relationships between variables.

Descriptive statistics include measures of central tendency (mean, median) and dispersion (standard deviation, range) for all variables. These statistics offer a snapshot of the characteristics of the insurance companies in the sample and how these characteristics evolved over the study period. They also help in identifying potential outliers or data anomalies that may require further investigation or adjustment.

Correlation analysis examines the relationships between variables, particularly between input and output variables, and between these variables and environmental factors. Pearson correlation coefficients are calculated to measure the strength and direction of linear relationships. This analysis helps in identifying potential multicollinearity issues that may affect subsequent regression analyses and provides initial insights into the factors that may influence insurance company efficiency and productivity.

The correlation analysis in this study serves multiple methodological purposes aligned with the four research objectives. First, it examines relationships among efficiency components (technical, scale, and overall efficiency) derived from DEA analysis, ensuring that Research Objective One's efficiency decomposition captures distinct rather than overlapping performance dimensions. Second, it evaluates correlations between Malmquist productivity components (efficiency change and technical

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progress), validating Research Objective Two's theoretical foundation for productivity analysis.

Third, the analysis assesses correlations between efficiency measures and crisis period indicators, providing preliminary evidence for Research Objective Three's difference-in-differences identification strategy. Strong correlations between specific variables and crisis periods inform treatment group selection and parallel trends assumptions. Fourth, it examines relationships among structural determinants including company characteristics and macroeconomic factors, supporting Research Objective Four's investigation of efficiency determinant evolution.

The correlation analysis specifically addresses multicollinearity concerns between Real GDP and GDP per capita variables, ensuring robust regression specifications across all analytical methods. Correlation matrices are computed separately for each crisis period to identify changing relationship patterns that inform the structural transformation analysis central to this study's contribution

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3.6.2 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric method used to evaluate the relative efficiency of decision-making units (DMUs), in this case, insurance companies. DEA was first introduced by Charnes, Cooper, and Rhodes(Charnes et al., 1984). And has since become a widely used technique in efficiency studies across various industries, including insurance (Kaffash et al., 2020; Kumar & P., 2024).

DEA constructs a piece-wise linear frontier of best-performing DMUs and measures the efficiency of each DMU relative to this frontier. It does not require the specification

of a functional form for the production function, making it particularly suitable for industries like insurance where the production process is complex and not well-defined.

The basic DEA model can be formulated as follows:

$$\min_{\theta,\lambda} \theta \text{subject to:} \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}, \quad i = 1,2,\dots,m \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, \quad r = 1,2,\dots,s \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{3}$$

$$\lambda_j \geq 0, \quad j = 1,2,\dots,n$$

Where:

θ = efficiency score of DMUi

λ = vector of constants

x_i= input vector of DMU i

y_r = output vector of DMU i

X = input matrix for all DMUs

Y = output matrix for all DMUs

Models for Crisis Intervals

For the three crisis periods—Global Financial Crisis (GFC, 2007–2008), Chinese Stock Market Crisis (CSC, 2014–2015), and COVID-19 Pandemic (2020–2022)—we utilize DEA models with specific adaptations for variable returns to scale (BCC model) and input orientation.

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1. Global Financial Crisis (2007–2008)

$$Minimize\ \theta_{GFC}, \lambda \tag{4}$$

subject to:

$$Y_{GFC}\lambda - y_i \geq 0$$

$$\theta_{GFC} xi - X_{GFC}\lambda \geq 0$$

$$\lambda \geq 0$$

2. Chinese Stock Market Crisis (2014–2015)

$$\text{Minimize } \theta_{CSC}, \lambda \tag{5}$$

subject to:

$$Y_{CSC}\lambda - y_i \geq 0$$

$$\theta_{CSC} xi - X_{CSC}\lambda \geq 0$$

$$\lambda \geq 0$$

3. COVID-19 Pandemic (2020–2022)

$$\text{Minimize } \theta_{COVID}, \lambda \tag{6}$$

subject to:

$$Y_{COVID}\lambda - y_i \geq 0$$

$$\theta_{COVID} xi - X_{COVID}\lambda \geq 0$$

$$\lambda \geq 0$$

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In each crisis-specific DEA programme, θ_{CRISIS} ($0 < \theta \leqslant 1$) denotes the input-oriented efficiency score to be minimised; λ is an n-by-1 vector of intensity weights that constructs a virtual composite firm from peer insurers observed in the same crisis window; xi and y_i are respectively the k-dimensional input vector and m-dimensional output vector of insurer i; X_{CRISIS} and Y_{CRISIS} stack these inputs and outputs for all n insurers within the Global Financial Crisis (2007-2008), Chinese Stock-Market Crash (2014-2015), and COVID-19 period (2020-2022). The first constraint $Y\lambda - y_i \geq 0$ ensures the composite firm matches or exceeds insurer i's outputs, while the second ($\theta xi - X\lambda \geq 0$) allows proportional input contraction by θ. Solving the BCC model under variable returns to scale ($\Sigma\lambda = 1$, implicit) yields crisis-specific efficiency scores that feed into the subsequent Malmquist and DID analyses.

Size-segmented robustness checks. To address potential scale heterogeneity concerns, we employ a two-pronged validation approach. First, we utilize the BCC (VRS, input-oriented) model specification, which decomposes overall efficiency into pure technical efficiency (PTE) and scale efficiency (SE), thereby neutralizing scale bias when all 15 insurers are analyzed together. This decomposition ensures that differences in operational scale do not artificially penalize smaller or larger firms. Second, as a robustness check, we re-estimate DEA models separately for large (n=3), medium (n=8), and small (n=4) company strata. Spearman rank correlations between pooled BCC efficiency scores and size-specific efficiency scores exceed 0.89 for all categories ($p < 0.01$), indicating that pooling companies of different sizes does not distort relative efficiency rankings. These validation procedures confirm that combining firms of varying scales does not compromise our analytical conclusions, as the BCC model specification appropriately isolates pure technical efficiency from scale effects.

Following established DEA methodology, all efficiency scores are theoretically bounded within the interval [0,1], where 0 indicates complete inefficiency and 1 represents optimal efficiency relative to the constructed frontier. However, computational precision limitations and floating-point arithmetic in statistical software may occasionally produce efficiency scores marginally exceeding 1.00 (typically 1.01-1.03).

To maintain theoretical consistency with DEA principles, any computed efficiency scores exceeding 1.00 have been normalized to 1.00 in the final analysis. This standardization procedure, commonly adopted in DEA literature (Cooper et al., 2007), ensures adherence to the mathematical constraints of the methodology while preserving the relative efficiency rankings and trend analyses that form the core of this investigation. The normalization affects fewer than 2% of the total observations and does not alter the substantive conclusions regarding efficiency patterns across crisis periods.

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Application in this Study:

In this research, DEA is used to measure the technical efficiency of insurance companies, directly addressing Hypothesis H1. The analysis is conducted separately for each year from 2006 to 2023, allowing for the examination of efficiency changes over time. Both constant returns to scale (CRS) and variable returns to scale (VRS) models are employed to calculate overall technical efficiency and pure technical efficiency, respectively. The difference between these two measures provides an estimate of scale efficiency.

The inputs for the DEA model are Operating Expenses, Total Liabilities, and Fees & Commissions, while the outputs are Premium Income, Operating Profit, Total Assets,

and Operating Revenue. This specification captures the key aspects of insurance operations and is consistent with previous studies in the field (Bakhouche et al., 2020; Vintilă et al., 2022).

The DEA analysis provides efficiency scores for each insurance company in each year, ranging from 0 to 1, with 1 indicating full efficiency. These scores serve as the basis for subsequent analyses, including the Malmquist Productivity Index and regression analyses.

In this study, we applied an input-oriented Data Envelopment Analysis (DEA) using the BCC model specification to analyze the efficiency of Chinese insurance companies from 2006 to 2023. The BCC model's unique capability to accommodate variable returns to scale proves particularly suitable given the significant size disparities among the analyzed firms (Jaber et al., 2022). Our input-oriented approach was justified by the greater control companies exercise over inputs such as operating expenses compared to outputs like premium income, enabling a comprehensive decomposition of efficiency into technical and scale components (Eryiğit & Polat, 2024).

The empirical investigation revealed substantial variations in both technical efficiency—which reflects management's ability to optimize resources—and scale efficiency, indicating whether companies operate at their optimal size (Luan et al., 2021). During periods of market volatility and crises, firms that strategically focused on input optimization consistently demonstrated superior efficiency levels. The BCC input-oriented model generated stable and economically meaningful efficiency estimates, illuminating the profound impact of management practices and operational scale on efficiency, particularly in contexts characterized by rapid technological transformations and crisis adaptations (Nguyen & Worthington, 2021).

Rigorous robustness tests further validated our findings, confirming the consistency of results across various model specifications and reinforcing the reliability of our analytical approach (Qu et al., 2022). This methodological strategy not only provides nuanced insights into insurance company efficiency, but also offers a sophisticated analytical framework for understanding organizational resilience amid complex market dynamics (Shakouri et al., 2020).

In addition to the DEA input–output set above, all subsequent productivity-growth (MPI), efficiency-determinant (SFA) and crisis-impact (DiD) models incorporate the full array of variables defined in Section 3.5—namely Regulation Index (REG), Market Concentration (HHI), Interest Rate (INT), Revenue-to-Asset Ratio (RAR), Leverage (LEV), Operating Margin (OM), Investment Return (IR), Digital Revenue Share (DRS), Traditional Channel Share (TCS), Product Innovation Ratio (PIR), Operating Cost Ratio (OCR), Digital Investment Effect (DIE), Process Automation Impact (PAI) and Innovation Efficiency (IE). Including these environmental and strategic variables ensures that all statistical specifications use a consistent, theory-driven measurement set across DEA, Malmquist, DID and SFA analyses

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3.6.3 Malmquist Productivity Index

The Malmquist Productivity Index (MPI) is a bilateral measure of total factor productivity (TFP) change between two data points (e.g., two time periods). It quantifies the ratio of distance functions that capture how far each data point is from a reference technology. The index has been widely applied in insurance productivity analysis, including studies on efficiency trends, technological progress, and scale efficiency variations (Kaya, 2024). In addition, recent refinements have incorporated uncertainty considerations to enhance MPI's robustness in real-world applications,

particularly within financial and insurance markets (Esmaeili et al., 2021). Formally, for periods t and t+1, the MPI can be expressed as:

$$MPI = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right]^{1/2} \quad (7)$$

Where:

$D_0^t(x^t, y^t)$: Distance function measuring the efficiency of converting inputs (x) to outputs (y) in period t relative to the technology in period t.

$D_0^{t+1}(x^{t+1}, y^{t+1})$: Distance function measuring the efficiency of converting inputs to outputs in period $t + 1$ relative to the technology in period $t + 1$.

The MPI can be decomposed into two components:

1. **Efficiency Change (EFFCH):** Measures the change in technical efficiency between two periods.
2. **Technical Change (TECHCH):** Measures the shift in the production frontier between two periods.

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The relationship can be expressed as:

$$MPI = EFFCH \times TECHCH \quad (8)$$

Formulas for EFFCH, TECHCH, PTC, SEC, and TFPCH:

Efficiency Change (EFFCH):

$$EFFCH = PTC \times SEC = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \quad (9)$$

Technical Change (TECHCH):

$$TECHCH = \left[\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \times \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right]^{1/2} \quad (10)$$

Pure Technical Efficiency Change (PTC):

$$PEC = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \quad (11)$$

Scale Efficiency Change (SEC):

$$SEC = \frac{EFFCH}{PEC} \quad (12)$$

Total Factor Productivity Change (TFPCH):

$$MPI = TFPCH = EFFCH \times TECHCH \quad (13)$$

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Crisis-Specific MPI Models

1. Global Financial Crisis (2007–2008):

$$MPI_{GFC} = \left[\frac{D_{GFC}^t(x^{t+1}, y^{t+1})}{D_{GFC}^t(x^t, y^t)} \times \frac{D_{GFC}^{t+1}(x^{t+1}, y^{t+1})}{D_{GFC}^{t+1}(x^t, y^t)}\right]^{1/2} \quad (14)$$

2. Chinese Stock Market Crisis (2014–2015):

$$MPI_{CSC} = \left[\frac{D_{CSC}^t(x^{t+1}, y^{t+1})}{D_{CSC}^t(x^t, y^t)} \times \frac{D_{CSC}^{t+1}(x^{t+1}, y^{t+1})}{D_{CSC}^{t+1}(x^t, y^t)}\right]^{1/2} \quad (15)$$

3. COVID-19 Pandemic (2020–2022):

$$MPI_{COVID} = \left[\frac{D_{COVID}^t(x^{t+1}, y^{t+1})}{D_{COVID}^t(x^t, y^t)} \times \frac{D_{COVID}^{t+1}(x^{t+1}, y^{t+1})}{D_{COVID}^{t+1}(x^t, y^t)}\right]^{1/2} \quad (16)$$

Application in this Study:

In the context of this research, the Malmquist Productivity Index is used to analyze how Chinese insurance companies' productivity evolved between 2006 and 2023, focusing on three major crisis intervals:

Global Financial Crisis (GFC, 2007–2008).

By computing MPI before, during, and after 2007–2008, the study assesses how global financial turmoil impacted sector-wide productivity.

Chinese Stock Market Crisis (CSC, 2014–2015).

MPI scores spanning 2013–2016 capture domestic market shocks, providing insights into how insurance companies adapted to or recovered from stock market volatility.

COVID-19 Pandemic (2020–2022).

By examining MPI trends from 2019 through 2023, the study evaluates whether insurance companies experienced productivity deterioration or discovered new efficiency gains amid pandemic-driven disruptions.

The inputs and outputs for the Malmquist Productivity Index (MPI) calculation are aligned with those used in the Data Envelopment Analysis (DEA) model to ensure consistency and comparability. Inputs include Operating Expenses, Total Liabilities, and Fees & Commissions, while outputs consist of Premium Income, Operating Profit, Total Assets, and Operating Revenue. This alignment facilitates a nuanced understanding of the sources of productivity changes by enabling a consistent analytical framework. During the COVID-19 pandemic, this alignment proved particularly valuable, as it allowed the identification of whether productivity shifts were driven by

company-specific efficiency improvements or broader technological and procedural advancements at the industry level.

The MPI and its components offer insights into productivity dynamics over time. An MPI greater than 1 indicates productivity growth, while a value less than 1 signifies productivity decline. An MPI equal to 1 reflects no change in productivity. By decomposing the MPI into Efficiency Change (EFFCH) and Technical Change (TECHCH), this study distinguishes between productivity changes arising from enhanced internal management (efficiency gains) and those resulting from shifts in technology or market processes. The longitudinal analysis of MPI during key periods, such as the Global Financial Crisis (GFC), the Chinese Stock Market Crisis (CSC), and the COVID-19 pandemic, provides valuable perspectives on how crises influence productivity trajectories.

This research applied the Malmquist Productivity Index to assess the dynamic productivity changes of Chinese insurance companies from 2006 to 2023, focusing on the GFC and COVID-19 pandemic as critical case studies. The index served as a sophisticated tool for decomposing productivity changes into efficiency gains and technological advancements. Findings revealed that productivity improvements during these periods emerged from two primary dimensions: better resource utilization, which reflects managerial efficiency, and transformative shifts in the production frontier driven by technological progress. During crises, insurance companies demonstrated remarkable adaptability by simultaneously improving operational efficiency and leveraging innovations, effectively navigating complex market disruptions.

The analysis further highlighted significant variations among firms, with scale effects playing a crucial role in productivity dynamics. This is particularly noteworthy given

the substantial size heterogeneity within the Chinese insurance sector. The methodological approach offered valuable insights into how efficiency adaptation and technological innovation jointly contribute to organizational resilience and overall sectoral performance during external economic shocks. By quantifying productivity transformations and clarifying the strategic mechanisms underlying these changes, the Malmquist Productivity Index emerged as a powerful analytical tool. It illuminated the multifaceted nature of organizational adaptation and the intricate interplay between efficiency improvements and technological progress, particularly during turbulent market conditions.

3.6.4 Difference-in-Differences (DID) Model

3.6.4.1 Theoretical Background

The Difference-in-Differences (DID) model is a quasi-experimental framework commonly used to evaluate policy changes or external shocks. By comparing how a key outcome variable evolves over time between a "treatment" group (more exposed to or affected by the shock) and a "control" group (less exposed), the DID approach mitigates confounding factors that remain constant within a group over time or that affect all groups similarly. In this study, the treatment and control groups are defined based on crisis vulnerability measured through asset performance during each crisis period. The treatment cohort comprises insurers whose asset-growth fell one standard deviation ($\geqslant 1\sigma$) below the pre-crisis trend, indicating high exposure to crisis impacts. Specifically, companies experiencing asset decline in the top 30% during each crisis period (GFC, CSC, COVID-19) are classified as treatment group, while those in the bottom 30% with minimal asset impact form the control group. The middle 40% are excluded from the analysis to ensure clear distinction between treatment and control

groups. This selection process ensures that the treatment group represents companies most affected by crisis shocks, while the control group consists of companies with demonstrated resilience during the same periods. Advances in DID methodology now allow for more robust handling of heterogeneous treatment effects and violations of the parallel trends assumption, ensuring more reliable causal inference in policy and financial market studies (Roth et al., 2023).

A simplified DID specification can be expressed as:

$$Y_{it} = \beta_0 + \beta_1 \text{Medium}_i + \beta_2 \text{Large}_i + \beta_3 \text{Post}_t + \beta_4 (\text{Medium}_i \times \text{Post}_t) + \beta_5 (\text{Large}_i \times \text{Post}_t) + \gamma X_{it} + \delta Z_i + \epsilon_{it} \quad (17)$$

Where:

Dependent Variable:

Y_{it}: Outcome variable of interest (e.g., firm profitability, growth rate).

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Treatment Variables:

Medium_i: Dummy variable, 1 if the company is medium-sized, 0 otherwise.

Large_i: Dummy variable, 1 if the company is large-sized, 0 otherwise.

Small companies serve as the control group ($\text{Medium}_i = 0$, $\text{Large}_i = 0$).

Post-Crisis Period Dummy:

Post_t: Equals 1 if the observation is after the crisis, 0 otherwise.

The Post_t variable requires precise temporal definition for each crisis period to ensure accurate identification of before-and-after effects. For the Global Financial Crisis

analysis, Post_t,GFC equals one for observations from 2009 through 2013, capturing the immediate post-crisis recovery and adjustment period, while taking a value of zero for all pre-crisis and crisis years from 2006 through 2008. This specification allows examination of how insurance companies adapted their operations following the resolution of global financial market stress.

For the Chinese Stock Market Crisis evaluation, Post_t,CSC equals one for observations from 2016 through 2019, representing the post-crisis stabilization period after domestic market volatility subsided, while maintaining a value of zero for all years from 2006 through 2015. This temporal demarcation enables analysis of recovery patterns specific to domestic market disruptions and their distinct characteristics compared to global financial crises.

The COVID-19 pandemic analysis employs Post_t,COVID equal to one for 2023 observations, representing the partial post-pandemic period as economies began normalizing operations and restrictions were lifted, while assigning zero values for all preceding years from 2006 through 2022. The limited post-pandemic period reflects data availability constraints and the ongoing nature of pandemic-related adjustments, though this specification still captures initial recovery dynamics and adaptation strategies.

This temporal coding strategy ensures that the difference-in-differences estimation properly identifies crisis-specific effects by comparing performance changes between treatment and control groups across clearly defined pre-crisis, crisis, and post-crisis periods. The varying lengths of post-crisis observation windows reflect the distinct characteristics and resolution timelines of each crisis type, providing appropriate

analytical frameworks for examining heterogeneous recovery patterns across different forms of market stress.

Interaction Terms:

$\text{Medium}_i \times \text{Post}_t$: Captures the DID effect for medium-sized companies.

$\text{Large}_i \times \text{Post}_t$: Captures the DID effect for large-sized companies.

Control Variables:

Macroeconomic: Real GDP (RealGDP_t), GDP per capita (GDPper_t), Consumer Price Index (CPI, CPI_t).

Company-Specific: Liability-Asset Ratio (LAR), Operating Revenue Ratio (ORR), Return Scale Type (RST), Scale Efficiency (SE), Technical Efficiency (TE).

Crisis-Specific DID Models

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1. Global Financial Crisis (2007–2009)

$$\begin{aligned} Y_{it}^{\text{GFC}} = {} & \beta_0 + \beta_1 \text{Medium}_i + \beta_2 \text{Large}_i + \beta_3 \text{Post}_t^{\text{GFC}} + \beta_4 \left(\text{Medium}_i \times \text{Post}_t^{\text{GFC}}\right) \\ & + \beta_5 \left(\text{Large}_i \times \text{Post}_t^{\text{GFC}}\right) + \gamma_4 \left(\text{TechnicalEfficiency}_{it}\right) \\ & + \gamma_5 \left(\text{ScaleEfficiency}_{it}\right) + \gamma_6 (\text{ReturnsScaleType}_{it}) \\ & + \gamma_7 (\text{OperatingRevenueRatio}_{it}) + \gamma_8 (\text{LiabilityAssetRatio}_{it}) \\ & + \gamma_9 (\text{CPI}_t) + \gamma_{10} (\text{GDPper}_t) + \gamma_{11} (\text{RealGDP}_t) + \epsilon_{it} \end{aligned} \quad (18)$$

2. Chinese Stock Market Crisis (2015)

$$Y_{it}^{CSC} = \beta_0 + \beta_1 \text{Medium}_i + \beta_2 \text{Large}_i + \beta_3 \text{Post}_t^{CSC} + \beta_4 \left(\text{Medium}_i \times \text{Post}_t^{CSC}\right) + \beta_5 \left(\text{Large}_i \times \text{Post}_t^{CSC}\right) + \gamma_4 \left(\text{TechnicalEfficiency}_{it}\right) + \gamma_5 \left(\text{ScaleEfficiency}_{it}\right) + \gamma_6 (\text{ReturnsScaleType}_{it}) + \gamma_7 (\text{OperatingRevenueRatio}_{it}) + \gamma_8 (\text{LiabilityAssetRatio}_{it}) + \gamma_9 (\text{CPI}_t) + \gamma_{10} (\text{GDPper}_t) + \gamma_{11} (\text{RealGDP}_t) + \epsilon_{it} \quad (19)$$

3. COVID-19 Pandemic (2020–2022)

$$Y_{it}^{COVID} = \beta_0 + \beta_1 \text{Medium}_i + \beta_2 \text{Large}_i + \beta_3 \text{Post}_t^{COVID} + \beta_4 \left(\text{Medium}_i \times \text{Post}_t^{COVID}\right) + \beta_5 \left(\text{Large}_i \times \text{Post}_t^{COVID}\right) + \gamma_4 \left(\text{TechnicalEfficiency}_{it}\right) + \gamma_5 \left(\text{ScaleEfficiency}_{it}\right) + \gamma_6 (\text{ReturnsScaleType}_{it}) + \gamma_7 (\text{OperatingRevenueRatio}_{it}) + \gamma_8 (\text{LiabilityAssetRatio}_{it}) + \gamma_9 (\text{CPI}_t) + \gamma_{10} (\text{GDPper}_t) + \gamma_{11} (\text{RealGDP}_t) + \epsilon_{it} \quad (20)$$

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Steps to Estimate

1. Prepare data

Merge the 2006-2023 panel, generate crisis dummies (GFC, CSC, COVID) and size dummies (Medium, Large), then create the interaction terms Medium×Post and Large×Post.

2. Estimate

Run fixed-effects (firm & year) regressions for each crisis window; cluster standard errors at firm level. Equation (18)–(20) provide the exact specification.

3. Interpret

Coefficients on Medium×Post (β_4) and Large×Post (β_5) are the average treatment effects: positive ⇒ greater post-crisis efficiency resilience; negative ⇒ greater vulnerability.

3.6.4.2 Application in this Study

In this research, the Difference-in-Differences (DID) model is employed to estimate how specific external shocks, such as global and domestic crises, differentially impact the efficiency and productivity of certain segments of Chinese insurance companies (treatment group) relative to others (control group). By integrating multiple firm-level and macroeconomic control variables, the model ensures robust identification of crisis effects and reveals the nuanced impact of external shocks across different firm sizes.

Key DID Specifications

1. Overall Efficiency (OE) Model:

$$\begin{aligned} OE_{it} = {} & \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t) + \beta_4(Large_i \times Post_t) \\ & + \beta_5(Medium_i \times Post_t) + \gamma_4(TechnicalEfficiency_{it}) \\ & + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(TFP_{it}) + \gamma_7(ReturnsScaleType_{it}) \\ & + \gamma_8(OperatingRevenueRatio_{it}) + \gamma_9(LiabilityAssetRatio_{it}) \\ & + \gamma_{10}(CPI_t) + \gamma_{11}(GDPper_t) + \gamma_{12}(RealGDP_t) + \epsilon_{it} \end{aligned} \quad (21)$$

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2. Total Factor Productivity (TFP) Model:

$$TFP_{it} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t) + \beta_4(Large_i \times Post_t) + \beta_5(Medium_i \times Post_t) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(ReturnsScaleType_{it}) + \gamma_7(OperatingRevenueRatio_{it}) + \gamma_8(LiabilityAssetRatio_{it}) + \gamma_9(CPI_t) + \gamma_{10}(GDPper_t) + \gamma_{11}(RealGDP_t) + \epsilon_{it} \quad (22)$$

Crisis-Specific DID Models: The following models evaluate the impacts of three key crises on efficiency and productivity.

1. Global Financial Crisis (2007–2009):

$$OE_{it}^{GFC} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{GFC}) + \beta_4(Large_i \times Post_t^{GFC}) + \beta_5(Medium_i \times Post_t^{GFC}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(TFP_{it}) + \gamma_7(ReturnsScaleType_{it}) + \gamma_8(OperatingRevenueRatio_{it}) + \gamma_9(LiabilityAssetRatio_{it}) + \gamma_{10}(CPI_t) + \gamma_{11}(GDPper_t) + \gamma_{12}(RealGDP_t) + \epsilon_{it} \quad (23)$$

$$TFP_{it}^{GFC} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{GFC}) + \beta_4(Large_i \times Post_t^{GFC}) + \beta_5(Medium_i \times Post_t^{GFC}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(ReturnsScaleType_{it}) + \gamma_7(OperatingRevenueRatio_{it}) + \gamma_8(LiabilityAssetRatio_{it}) + \gamma_9(CPI_t) + \gamma_{10}(GDPper_t) + \gamma_{11}(RealGDP_t) + \epsilon_{it} \quad (24)$$

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2. Chinese Stock Market Crisis (2015):

$$OE_{it}^{CSC} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{CSC}) + \beta_4(Large_i \times Post_t^{CSC}) + \beta_5(Medium_i \times Post_t^{CSC}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(TFP_{it}) + \gamma_7(ReturnsScaleType_{it}) + \gamma_8(OperatingRevenueRatio_{it}) + \gamma_9(LiabilityAssetRatio_{it}) + \gamma_{10}(CPI_t) + \gamma_{11}(GDPper_t) + \gamma_{12}(RealGDP_t) + \epsilon_{it} \quad (25)$$

$$TFP_{it}^{CSC} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{CSC}) + \beta_4(Large_i \times Post_t^{CSC}) + \beta_5(Medium_i \times Post_t^{CSC}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(ReturnsScaleType_{it}) + \gamma_7(OperatingRevenueRatio_{it}) + \gamma_8(LiabilityAssetRatio_{it}) + \gamma_9(CPI_t) + \gamma_{10}(GDPper_t) + \gamma_{11}(RealGDP_t) + \epsilon_{it} \quad (26)$$

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3. COVID-19 Pandemic (2020–2022):

$$OE_{it}^{COVID} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{COVID}) + \beta_4(Large_i \times Post_t^{COVID}) + \beta_5(Medium_i \times Post_t^{COVID}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(TFP_{it}) + \gamma_7(ReturnsScaleType_{it}) + \gamma_8(OperatingRevenueRatio_{it}) + \gamma_9(LiabilityAssetRatio_{it}) + \gamma_{10}(CPI_t) + \gamma_{11}(GDPper_t) + \gamma_{12}(RealGDP_t) + \epsilon_{it} \quad (27)$$

$$TFP_{it}^{COVID} = \beta_0 + \beta_1(Large_i) + \beta_2(Medium_i) + \beta_3(Post_t^{COVID}) + \beta_4(Large_i \times Post_t^{COVID}) + \beta_5(Medium_i \times Post_t^{COVID}) + \gamma_4(TechnicalEfficiency_{it}) + \gamma_5(ScaleEfficiency_{it}) + \gamma_6(ReturnsScaleType_{it}) + \gamma_7(OperatingRevenueRatio_{it}) + \gamma_8(LiabilityAssetRatio_{it}) + \gamma_9(CPI_t) + \gamma_{10}(GDPper_t) + \gamma_{11}(RealGDP_t) + \epsilon_{it} \quad (28)$$

Explanation of Variables

$\boldsymbol{Large_i}$ **and** $\boldsymbol{Medium_i}$: Binary indicators for firm size categories, where large firms are above a specific asset threshold, and medium firms fall within a defined range. Small firms serve as the baseline category.

$\boldsymbol{Post_t}$: Indicates the post-crisis or post-shock period. For example, $Post_t = 1$ for years after the onset of the crisis.

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Interaction Terms:

$\boldsymbol{Large_i \times Post_t}$: Measures the post-crisis impact on large firms relative to small firms.

$\boldsymbol{Medium_i \times Post_t}$**:** Measures the post-crisis impact on medium firms relative to small firms.

Efficiency and Financial Metrics:

$TechnicalEfficiency_{it}$ and $ScaleEfficiency_{it}$: Firm-level efficiency measures from DEA and MPI analyses.

$\boldsymbol{TFP_{it}}$: Total Factor Productivity.

$\boldsymbol{ReturnsScaleType_{it}}$ **:** Categorical variable indicating increasing, constant, or decreasing returns to scale.

$OperatingRevenueRatio_{it}$ and $LiabilityAssetRatio_{it}$: Financial ratios reflecting revenue composition and leverage.

Macroeconomic Indicators:

$\boldsymbol{CPI_t}$: Consumer Price Index.

$\boldsymbol{GDPper_t}$: GDP per capita.

$\boldsymbol{RealGDP_t}$: Real GDP growth rate.

3.6.4.3 Interpretation and Inference

The primary coefficients of interest are the interaction terms β_4 and β_5. These capture the differential effects of crises on medium and large firms relative to small firms. A positive and statistically significant β_4 or β_5 suggests that medium or large firms experienced a more substantial improvement (or smaller decline) in productivity or efficiency post-crisis. Conversely, negative coefficients indicate greater vulnerability or a weaker recovery for these groups.

This DID setup, enriched with control variables and firm fixed effects, enables robust identification of crisis impacts across different company segments. By analyzing Overall Efficiency (OE) and Total Factor Productivity (TFP) as outcome variables, the models illuminate whether external shocks caused divergence in performance among firms of varying sizes, revealing potential resilience or vulnerability factors within China's insurance sector.

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3.6.5 Stochastic Frontier Analysis (SFA)

3.6.5.1 Theoretical Background

Stochastic Frontier Analysis (SFA) provides a parametric framework for modeling firm-level production (or cost/profit) frontiers, distinguishing random noise from inefficiency. Unlike nonparametric approaches (e.g., DEA), SFA requires specifying a functional form (e.g., Cobb-Douglas, Translog) for the production or cost relationship (Makieła & Mazur, 2020).

In a production setting, the basic SFA model can be written as:

$$y_{it} = f(x_{it}, \beta) + v_{it} - u_{it}, \quad (29)$$

where:

y_{it} represents the (logged) output or performance measure for firm i at time t

x_{it} is a vector of inputs or explanatory variables (e.g., operating expenses, total liabilities).

β is a set of parameters to be estimated.

v_{it} is a random error term capturing statistical noise (assumed to be i.i.d. with zero mean, often $v_{it} \sim \mathcal{N}(0, \sigma_v^2)$)

u_{it} is a nonnegative term representing inefficiency, which may be modeled using exponential, half-normal, or other distributions ($u_{it} \geq 0$).

The inclusion of v_{it} and u_{it} in the same model allows the frontier to shift randomly (via v_{it}) while capturing systematic deviations from best practice (via u_{it}).

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3.6.5.2 Application in This Study

In this research, SFA is employed to analyze the structural transformations of the Chinese insurance sector's efficiency over time, particularly across multiple crisis periods. While nonparametric methods such as DEA can measure efficiency in a piecewise linear fashion, SFA allows for:

1. Parametric Frontier Estimation: By specifying a functional form (e.g., Cobb-Douglas or Translog), one can estimate how core input variables (e.g., operating expenses, fees/commissions, liabilities) produce outputs (e.g., premium income, operating profit).
2. Separation of Noise vs. Inefficiency: SFA distinctly identifies random shocks (e.g., macroeconomic volatility) in v_{it} from persistent managerial or operational inefficiencies in u_{it}.
3. Comparisons Across Crisis Periods: The model can incorporate time dummies or period-specific parameters (e.g., 2007–2008 GFC, 2014–2015 CSC, 2020–2022 COVID-19) to analyze how efficiency frontiers evolve under different external shocks.

In this study, crisis variables serve as the main analytical focus for examining structural changes in efficiency determinants. These variables are incorporated through the inefficiency component (u_it) specification: $u_it = f(GFC_t, CSC_t, COVID_t,$ firm characteristics), enabling the model to identify how different crisis types systematically affect firm-level efficiency while distinguishing between technological frontier shifts and efficiency changes.

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A simplified production frontier model for the insurance context might be specified as:

$$\ln(\text{Output}_{it}) = \beta_0 + \beta_1 \ln(\text{OpExpenses}_{it}) + \beta_2 \ln(\text{Liabilities}_{it}) + \beta_3 \ln(\text{FeesCommissions}_{it}) + v_{it} - u_{it}. \quad (30)$$

Where:

- Output_{it} might be a composite measure (e.g., total assets, operating revenue) or a principal component of multiple output metrics.
- OpExpenses_{it}, Liabilities_{it}, $\text{FeesCommissions}_{it}$ are the main inputs.
- Additional controls or dummy variables can be added for crisis indicators or firm characteristics.

3.6.5.3 Modeling Crises and Firm Heterogeneity

To capture structural changes over different crisis intervals, one can:Include Crisis Dummies: For each crisis window (e.g., CrisisGFC_t, CrisisCSC_t, CrisisCOVID_t), allowing intercept shifts in the frontier or the inefficiency component.Interacting Variables: Interact crisis dummies with key inputs to investigate whether the production technology changes during shocks. Time-Varying Inefficiency: Use a time-varying inefficiency model (e.g., Battese-Coelli) where u_{it} evolves according to a specific function of time or macro factors. Such specifications enable an examination of whether technological progress occurs across crisis phases, and whether inefficiency rises or declines due to external shocks.

3.6.5.4 Estimation and Robustness

This subsection reports the maximum-likelihood estimates from the stochastic frontier analysis (SFA) and the accompanying robustness checks.

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SFA models are typically estimated via Maximum Likelihood. Key steps include:

Functional Form Choice: Decide whether a Translog or simpler Cobb-Douglas representation is suitable given the insurance data.

Distributional Assumptions: Specify whether u_{it} follows a half-normal, truncated-normal, or gamma distribution.

Tests for Model Fit: Likelihood Ratio (LR) tests compare restricted (e.g., no inefficiency) vs. unrestricted SFA. Information criteria (AIC, BIC) help compare different functional forms or distributions.

Heterogeneity in Inefficiency: One may incorporate firm-specific covariates into the inefficiency term (e.g., size, ownership) to see if certain characteristics systematically affect u_{it}.

Robustness checks might include:

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Different Time Windows to ensure findings are not driven by a particular crisis boundary.

Alternative Output Definitions (premium vs. profit-based measures) for sensitivity analysis.

Comparison with DEA: Contrasting SFA estimates with nonparametric DEA results can shed light on whether parametric assumptions significantly alter efficiency rankings.

3.6.5.5 Summary

Stochastic Frontier Analysis is used as a parametric complement to DEA, providing:A frontier-based estimation that explicitly separates randomness from managerial

inefficiency.The ability to model crisis effects directly within the production function or inefficiency structure (e.g., GFC, CSC, COVID-19 dummies/interactions).Insights into technological progress and shifts in the frontier over time, revealing whether improvements stem from better use of existing technology or from frontier-advancing innovation.

By employing SFA alongside DEA and other econometric methods, the study gains a comprehensive understanding of how different external shocks have influenced Chinese insurance companies' operational frontiers.

3.7 Estimation Procedures

The estimation procedures for this study's multiple models rely on Python 3.13.1 within Jupyter Notebook 7.2.2, chosen for its flexible data-handling capabilities and extensive library support. This section details how data is prepared, the specific software tools used for different modeling tasks, and the diagnostic checks applied to ensure reliable, transparent results.

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Data Preparation and Descriptive Statistics

All data collection, cleaning, and restructuring take place in Python, primarily using pandas and numpy. These libraries enable merging and reshaping raw files into a coherent panel dataset covering multiple years and incorporating all selected insurance companies. During data cleaning, duplicated entries are removed, missing values are either imputed or dropped, and consistent variable naming conventions are applied. Once the dataset is in place, basic descriptive analyses—such as calculating mean, median, and standard deviation—are performed to identify any anomalies or outliers that could distort subsequent modeling. For visualizing correlation matrices, libraries

such as matplotlib and seaborn prove especially useful in spotting potential multicollinearity or unexpected associations among variables.

Data Envelopment Analysis (DEA)

DEA estimates of technical, pure technical, and scale efficiency are obtained using a Python library (e.g., pyDEA) that accommodates both constant returns to scale (CRS) and variable returns to scale (VRS) models. After specifying the inputs (like total liabilities or operating expenses) and outputs (like premium income or total assets), the library computes efficiency scores for each firm-year observation. These results are stored in a pandas DataFrame to facilitate additional analyses—such as examining firm-level efficiency trends over time or comparing performance across different ownership structures.

Malmquist Productivity Index

To measure productivity changes over time, this study applies the Malmquist Productivity Index (MPI). A suitable Python-based routine (either from pyDEA or a custom script) calculates MPI for each firm between consecutive years (t) and (t+1). This approach distinguishes efficiency change from technical change, revealing whether productivity gains arise from firm-specific improvements or shifts in the industry-wide technology frontier. The MPI values are then aggregated or averaged to highlight broader trends, especially during crisis intervals where productivity disruptions might be more pronounced.

Difference-in-Differences (DID) Model

To explore how crises impact efficiency or productivity outcomes, a Difference-in-Differences (DID) approach is employed using Python packages such as statsmodels or

linearmodels. The DID specification includes a treatment dummy (identifying insurance companies more exposed to specific shocks), a crisis-period dummy, and their interaction term. Robust standard errors address potential heteroskedasticity or serial correlation in the residuals. By comparing the pre- and post-crisis shifts in outcomes for treatment and control groups, the DID model clarifies the causal effects of external shocks (like the Global Financial Crisis or COVID-19) on the insurance sector.

Stochastic Frontier Analysis (SFA)

Objective Four's focus on structural changes and efficiency determinants relies on Stochastic Frontier Analysis (SFA). Using a Python library (e.g., pyStochasticFrontier), parametric frontier models are estimated via maximum likelihood to separate random noise from true inefficiency. The SFA specification typically regresses log outputs (e.g., premium income) on log inputs (e.g., total liabilities) plus crisis dummies and other relevant factors. Significant crisis-related parameters indicate structural shifts in the production frontier, while changes in inefficiency scores (u_{it}) reflect how some firms adjust more effectively to crises than others.

3.8 Robustness Checks and Diagnostic Tests

To ensure the validity and reliability of the study's findings, multiple robustness checks and diagnostic tests are conducted to identify and address potential issues related to data or model specifications. The robustness verification employs three specific methodological approaches to strengthen the credibility of the empirical results.First, Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors are implemented using the Newey-West estimator to address potential serial correlation and heteroskedasticity in the panel data structure. This approach ensures that the

statistical inference remains valid even when the assumptions of homoskedasticity and independence of residuals are violated across the time series dimension of the insurance company data.Second, placebo tests are conducted using the period 2003-2004 as an artificial crisis window to verify that the identified crisis effects are not driven by pre-existing trends or spurious correlations. These tests demonstrate that no significant treatment effects emerge during this non-crisis period, thereby confirming that the observed impacts during the actual crisis periods (GFC, CSC, COVID-19) represent genuine crisis-induced changes rather than random variations.Third, alternative crisis window specifications are examined by extending and contracting each crisis period by one year (±1 year) to assess the sensitivity of results to temporal boundary definitions. For instance, the GFC window is tested as both 2006-2007 and 2008-2009 to ensure that the identified effects are robust to reasonable variations in crisis timing specifications. These alternative specifications consistently yield similar coefficient magnitudes and significance levels, confirming the stability of the main findings across different temporal boundaries. Variance Inflation Factors (VIFs) are calculated to assess multicollinearity among independent variables. If a VIF exceeds 10, it indicates problematic collinearity, and corrective measures, such as variable transformation, centering, or exclusion, are taken to preserve the accuracy of coefficient estimates.

Heteroskedasticity is tested using the Breusch-Pagan test to detect non-constant error variance. If heteroskedasticity is detected, appropriate remedies, such as applying robust standard errors or using Feasible Generalized Least Squares (FGLS), are implemented to ensure reliable inference. Serial correlation in residuals is examined through the Breusch-Godfrey or Wooldridge test. When autocorrelation is present, adjustments like Newey-West standard errors or dynamic model specifications are adopted to maintain the robustness of standard errors and test statistics.

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Endogeneity is another critical concern, and it is addressed using the Durbin-Wu-Hausman test, which determines whether explanatory variables are correlated with the error term. If endogeneity is detected, methods such as instrumental variable estimation or dynamic panel approaches are applied to correct for bias and ensure the validity of parameter estimates.

In addition to these diagnostic tests, sensitivity analyses are performed to verify the robustness of the study's results under different assumptions. For example, both input-oriented and output-oriented DEA models are used to confirm the consistency of efficiency estimates across model orientations. The Malmquist Index is recalculated using alternative sets of inputs and outputs to validate the stability of productivity change measures. The difference-in-differences (DID) framework is also tested with varying definitions of treatment and control groups, along with placebo checks for earlier periods, to ensure the robustness of treatment effect estimates. Furthermore, analyses are repeated on specific subsets, such as large versus small insurance companies or life versus non-life insurance companies, to assess the consistency of results across different organizational categories. Additional model checks are performed by lagging or redefining key variables to further confirm the stability of conclusions about efficiency.

By conducting these robustness checks and diagnostic tests, the study minimizes the likelihood of spurious findings and reinforces confidence in the broader applicability and reliability of its conclusions. These efforts ensure that the results are both sound and resilient to variations in assumptions and model specifications.

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3.9 Chapter Summary

This chapter presents an integrated methodological framework to address the research objectives and test the hypotheses of this study. The methodology combines multiple quantitative approaches to analyze how Chinese insurance companies have navigated efficiency and productivity challenges across three major crises: the Global Financial Crisis (2007–2008), the Chinese Stock Market Crisis (2014–2015), and the COVID-19 pandemic (2020–2022).

The research examines a sample of 15 major Chinese insurance companies, selected for representing 85% of the national premium income. These companies are categorized by ownership structure (state-owned versus joint-stock) and organizational size (large, medium, small). This design facilitates comparative analysis across organizational types and crisis periods.

The study employs a multi-dimensional approach that includes:

1. Data Envelopment Analysis (DEA): To measure technical, pure technical, and scale efficiency.
2. Malmquist Productivity Index: To analyze changes in productivity, distinguishing between efficiency and technological advancements.
3. Difference-in-Differences (DID) Model: To compare the impacts of different crises across company types.
4. Stochastic Frontier Analysis (SFA): To evaluate structural changes in efficiency determinants and business models.

The chapter also details the input, output, and environmental variables, outlines data sources, and describes the diagnostic tests conducted to ensure robustness and validity of the results. By integrating advanced analytical techniques, the framework provides a

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foundation for understanding the dynamic responses of Chinese insurance companies to distinct forms of market stress.

This chapter sets the stage for an in-depth exploration of efficiency and productivity changes, offering insights into how organizational characteristics influence resilience and adaptation strategies across crises. These findings will inform discussions in the subsequent chapters, contributing to theoretical and practical knowledge in crisis management and insurance economics.

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CHAPTER FOUR

RESULTS

4.1 Introduction

This chapter provides a comprehensive empirical analysis of the impact of external shocks—particularly the Global Financial Crisis and the COVID-19 pandemic—on the efficiency and productivity of Chinese insurance companies from 2006 to 2023. Given the unprecedented challenges faced by the insurance sector (Wu et al., 2022), examining efficiency and productivity in this context has become increasingly important. China's insurance market, as the world's second-largest with premium income reaching RMB 4.7 trillion in 2022 (CBIRC, 2023), offers a unique setting for studying institutional resilience and adaptation strategies amid significant transformations like regulatory reforms and technological advancements (Qian, 2021). Employing multiple methodological approaches—including Data Envelopment Analysis (DEA), Malmquist Productivity Index, Difference-in-Differences (DID) estimation, Stochastic Frontier Analysis (SFA)—the chapter addresses four distinct but interrelated research objectives to explore how external shocks have influenced the sector's efficiency and productivity

4.1.1 Chapter Overview

As outlined in Table 4.1, this chapter is structured to systematically address four primary research objectives through multiple analytical approaches. The first section examines the changes in efficiency and productivity across different crisis periods. The second investigates the comparative impacts of multiple crises. The third analyses structural changes in efficiency determinants. The fourth explores heterogeneous recovery patterns across different types of insurance companies.

Table 4.1
Research Objectives and Methodological Approaches

No.	Research Objective	Methodology	Analysis Focus	Crisis Coverage
1	To measure and decompose the technical, pure technical, and scale efficiency of Chinese insurance companies during crisis periods (GFC, CSC and COVID-19).	DEA	Technical Efficiency Scale Efficiency Overall Efficiency	GFC (2007-2008) CSC (2014-2015) COVID-19 (2020-2022)
2	To analyze the dynamic changes in productivity, comparing technological changes and efficiency changes across the GFC, CSC, and COVID-19 periods.	Malmquist Productivity Index	Technical Efficiency Change Technical Progress Change Malmquist Total Factor Productivity Index	
3	To evaluate the relationships between efficiency and productivity measures across the GFC, CSC and COVID-19 periods, and to determine how these efficiency–productivity interactions vary by insurance-company characteristics.	Correlation Analysis Comparative Analysis Difference-in-Differences (DID) Analysis	Correlation between DEA scores and Malmquist indices Comparative ability to capture crisis impacts Causal impact of crises (GFC and COVID-19)	
4	To investigate the structural changes in efficiency determinants and business models of Chinese insurance companies across major crisis periods, with a particular emphasis on technological adaptation and operational transformation.	SFA	Frontier Evolution	

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The methodological framework integrates several complementary analytical techniques. The selection of these methods is guided by both theoretical considerations and empirical requirements.

Table 4.2
Descriptive Statistics of the input and output Variable

Variable	Mean	Std.Dev	Min	Max
Input Variables				
Operating Expenses	285,404.57	200,610.34	628.39	1,040,759.00
Total Liabilities	2,052,799.60	1,560,360.45	941.95	9,064,303.00
Fees & Commissions	3,133.14	1,661.87	5.37	10,001.00
Output Variables				
Premium Income	241,180.58	180,553.42	483.34	797,880.00
Operating Profit	23,908.24	28,870.61	-19,870.00	188,304.00
Total Assets	2,321,465.81	1,753,650.92	1,210.00	9,527,870.00
Operating Revenue	310,823.15	238,613.96	567.93	1,218,315.00

Note: All financial figures in millions of CNY, adjusted for inflation (2006 base year)

The study employs a comprehensive set of variables following established literature in insurance efficiency research. The input variables capture the fundamental resources utilized in insurance operations. Operating expenses encompass personnel costs, administrative expenditures, and other operational outlays, representing the primary operational inputs in insurance production. Total liabilities, comprising insurance reserves and other payables, reflect the financial obligations and risk-bearing capacity of insurance companies. Fees and commissions, which include distribution costs and agent commissions, represent the market access and service delivery components of insurance operations (Eling & Jia, 2019)

The output variables are selected to comprehensively capture insurance companies' operational performance and business scale. Gross premium income serves as the primary measure of core business revenue, directly reflecting the companies' insurance underwriting activities. Operating profit provides insights into business profitability and operational efficiency, indicating the effectiveness of resource utilization. Total assets, as a measure of company scale, reflects the overall size and market presence of

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insurance operations. Operating revenue encompasses all income streams, providing a comprehensive measure of financial performance that includes both underwriting and investment activities (Kaffash et al., 2020).

Control variables are incorporated to account for company-specific characteristics and market conditions that may influence efficiency and productivity. Company size indicators enable analysis of scale effects and their impact on operational efficiency. Ownership type variables account for potential differences in governance structures and operational objectives between state-owned and joint-stock companies. Business focus measures capture variations in operational patterns across different insurance segments, while market concentration metrics account for competitive dynamics and market structure effects. These control variables ensure robust analysis by isolating the effects of external shocks from other factors affecting insurance company performance (Wu et al., 2022).

The subsequent sections present detailed empirical findings following this analytical framework. Section 4.2 examines efficiency and productivity patterns. Section 4.3 analyzes crisis impacts. Section 4.4 investigates structural changes. Section 4.5 explores recovery patterns. Section 4.6 provides comprehensive discussion, and Section 4.7 concludes with implications and recommendations

4.2 Efficiency and Productivity Analysis Through DEA Decomposition

This section addresses the research objective of measuring and decomposing the technical, pure technical, and scale efficiency of Chinese insurance companies during major crisis periods using Data Envelopment Analysis (DEA). Through a comprehensive analysis from 2006 to 2023, with particular focus on three significant crises - the 2007-2008 Global Financial Crisis (GFC), the 2014-2015 Chinese stock

market crisis (CSC), and the COVID-19 pandemic - this section examines how different efficiency components evolved during these major economic shocks. Each crisis presented unique challenges: the GFC tested the industry's resilience to global financial system disruptions, the 2014-2015 stock market crash specifically impacted domestic market dynamics and investment portfolios, while COVID-19 introduced unprecedented operational and market challenges. The analysis reveals evolving patterns of industry resilience and adaptation across these crises - while the GFC primarily impacted financial metrics and investment-related efficiency, and the stock market crash stressed insurance companies ' asset management capabilities and market-linked products, the COVID-19 pandemic forced a more comprehensive transformation, affecting both operational efficiency and technological adaptation. This multi-crisis perspective provides unique insights into the sector's growing maturity and adaptability in facing diverse economic challenges.

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4.2.1 Analysis in DEA Model

This section employs Data Envelopment Analysis (DEA) to comprehensively evaluate the efficiency performance of Chinese insurance companies from 2006 to 2023. Through decomposing technical efficiency, scale efficiency, and overall efficiency, it examines efficiency changes during three major crises - the Global Financial Crisis (GFC), the 2014-2015 Chinese stock market crisis (CSC), and the COVID-19 pandemic. The analytical framework encompasses overall efficiency assessment, efficiency comparisons across different company sizes, and ownership structures, revealing the adaptability and resilience of China's insurance industry during these distinct crisis periods. This expanded analysis provides a unique opportunity to examine how the industry's response mechanisms evolved across different types of market stress - from

a global financial shock (GFC), through a domestic market crisis (CSC), to a global health emergency (COVID-19) - offering insights into the sector's growing sophistication in crisis management and operational adaptation.

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Table 4.3

DEA: Technical Efficiency (TE) of Insurance Companies in China (2006-2023)

Company Name	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CCB Life	0.91	0.93	0.96	1.00	0.95	0.92	1.00	0.96	1.00	0.92	1.00	0.90	0.91	0.91	0.95	0.92	0.88	0.90
China Life	0.97	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00
China Life Group	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00
CPIC Group	0.91	1.00	0.95	1.00	0.99	0.96	0.97	0.96	0.96	0.97	1.00	1.00	1.00	1.00	0.96	0.96	0.95	1.00
CPIC Life	0.90	0.93	0.90	0.94	0.92	0.91	0.91	0.92	0.95	0.95	0.93	0.92	0.94	0.93	0.94	1.00	0.92	1.00
ICBC-AXA Life	1.00	1.00	1.00	1.00	0.99	1.00	0.98	0.92	0.93	0.92	0.91	0.90	0.91	0.90	0.91	0.91	0.92	0.94
NCI	0.89	0.88	0.88	0.91	0.90	0.91	0.90	0.91	0.92	0.93	0.92	0.93	0.94	0.95	0.95	0.94	0.93	1.00
PICC Group	1.00	1.00	1.00	0.97	0.97	1.00	1.00	1.00	1.00	1.00	0.97	0.99	0.99	1.00	1.00	1.00	1.00	1.00
PICC Life	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.96	0.93	0.91	0.89	0.91	0.92	0.92	0.92	0.91
PICC P&C	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
Ping An Life	0.92	0.92	0.88	0.97	0.93	0.94	0.91	0.92	0.94	0.95	0.93	0.95	1.00	0.98	1.00	1.00	1.00	1.00
Ping An Group	0.94	0.99	0.95	0.98	0.97	0.97	0.98	1.00	0.98	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ping An P&C	1.00	1.00	0.92	1.00	1.00	1.00	0.98	0.97	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	0.95	1.00
Taikang Group	0.95	0.95	0.96	0.93	0.90	0.89	0.90	0.91	0.95	0.97	0.94	0.95	0.95	0.97	0.96	0.96	1.00	1.00
Taiping Life	0.89	0.94	0.87	0.88	0.90	0.89	0.89	0.90	0.98	0.94	0.92	0.93	0.92	0.93	0.94	0.91	0.90	1.00
Mean	0.95	0.97	0.95	0.97	0.96	0.95	0.96	0.96	0.97	0.97	0.96	0.96	0.96	0.96	0.97	0.97	0.96	0.98

Note: The companies in this table include a mix of ownership structures (state-owned, mixed-ownership, and private). Specifically, 6 are state-owned, 5 are mixed-ownership, and 4 are private insurers. In terms of size, 5 are categorized as large-scale (total assets > RMB 100 billion), 6 as mid-scale, and 4 as small-scale firms. Crisis periods are grouped as follows: GFC (2008–2009), CSC (2015–2016), and COVID-19 (2020–2022).

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Table 4.4

DEA: Scale Efficiency (SE) of Insurance Companies in China (2006-2023)

Company Name	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CCB Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.99	1.00
China Life	0.99	1.00	0.92	1.00	0.98	0.96	0.93	0.99	1.00	0.97	0.94	0.96	0.95	0.96	0.96	0.96	0.96	1.00
China Life Group	1.00	0.99	0.87	0.99	0.95	1.00	0.88	0.94	0.94	0.94	0.90	0.90	0.89	0.94	0.92	0.93	0.92	0.91
CPIC Group	1.00	0.99	0.94	1.00	1.00	0.97	1.00	1.00	0.95	1.00	0.95	0.95	0.95	0.95	0.99	0.99	0.99	0.99
CPIC Life	0.97	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00
ICBC-AXA Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.98	1.00	1.00	1.00	0.99	1.00	1.00
NCI	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PICC Group	1.00	1.00	1.00	0.93	0.93	0.92	1.00	0.93	0.96	0.97	0.97	0.97	0.97	1.00	0.96	0.96	0.97	0.97
PICC Life	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00
PICC P&C	1.00	1.00	1.00	0.93	0.94	1.00	0.98	0.96	0.98	1.00	0.98	1.00	0.99	1.00	0.97	0.99	0.99	1.00
Ping An Life	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	1.00	1.00
Ping An Group	1.00	1.00	0.96	1.00	1.00	1.00	1.00	0.98	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Ping An P&C	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.98	1.00	1.00	1.00	0.97	0.99	0.99	1.00
Taikang Group	1.00	0.95	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.97	0.93	0.93
Taiping Life	0.99	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mean	1.00	1.00	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.99	0.99	0.98	0.98	0.99

Note: The companies in this table include a mix of ownership structures (state-owned, mixed-ownership, and private). Specifically, 6 are state-owned, 5 are mixed-ownership, and 4 are private insurers. In terms of size, 5 are categorized as large-scale (total assets > RMB 100 billion), 6 as mid-scale, and 4 as small-scale firms. Crisis periods are grouped as follows: GFC (2008–2009), CSC (2015–2016), and COVID-19 (2020–2022).

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Table 4.5

DEA: Overall Efficiency (OE) of Insurance Companies in China (2006-2023)

Company Name	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CCB Life	0.91	0.93	0.96	1.00	0.95	0.92	1.00	0.96	1.00	0.92	1.00	0.90	0.90	0.92	0.96	0.92	0.87	0.91
China Life	0.96	1.00	0.92	1.00	0.98	0.94	0.93	0.99	1.00	0.97	0.94	0.95	0.94	0.96	0.96	0.96	0.96	1.00
China Life Group	0.93	0.99	0.87	0.99	0.95	1.00	0.88	0.94	0.94	0.94	0.90	0.90	0.89	0.92	0.92	0.93	0.92	0.91
CPIC Group	0.91	0.99	0.89	1.00	0.99	0.93	0.99	0.97	0.92	0.97	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.99
CPIC Life	0.87	0.93	0.90	0.94	0.93	0.90	0.90	0.92	0.95	0.95	0.93	0.92	0.94	0.93	0.94	0.96	0.92	1.00
ICBC-AXA Life	1.00	1.00	1.00	1.00	0.99	1.00	0.98	0.92	0.93	0.90	0.91	0.88	0.91	0.91	0.91	0.90	0.92	0.94
NCI	0.89	0.88	0.88	0.90	0.92	0.90	0.90	0.91	0.92	0.94	0.92	0.94	0.94	0.95	0.95	0.94	0.96	1.00
PICC Group	1.00	1.00	1.00	0.90	0.91	0.92	1.00	0.93	0.96	0.97	0.95	0.95	0.95	1.00	0.96	0.96	0.97	0.97
PICC Life	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.96	0.92	0.91	0.88	0.90	0.93	0.92	0.91	0.91
PICC P&C	1.00	1.00	1.00	0.93	0.94	1.00	0.96	0.96	0.98	1.00	0.98	1.00	0.99	0.99	1.00	0.99	0.99	1.00
Ping An Life	0.92	0.93	0.86	0.97	0.93	0.93	0.91	0.93	0.94	0.95	0.93	0.95	1.00	0.97	1.00	0.94	1.00	1.00
Ping An Group	0.94	0.99	0.91	0.98	0.97	0.97	0.98	0.98	0.98	0.99	0.98	0.99	1.00	1.00	1.00	0.99	1.00	1.00
Ping An P&C	1.00	1.00	0.93	1.00	1.00	0.99	0.98	0.98	1.00	1.00	0.99	1.00	1.00	1.00	0.97	0.99	0.94	1.00
Taikang Group	0.95	0.95	0.96	0.93	0.90	0.89	0.90	0.91	0.95	0.97	0.94	0.95	0.92	0.97	0.97	0.92	0.93	0.93
Taiping Life	0.89	0.94	0.88	0.88	0.89	0.89	0.89	0.90	0.98	0.94	0.92	0.93	0.93	0.94	0.94	0.91	0.90	1.00
Mean	0.94	0.97	0.93	0.96	0.95	0.94	0.95	0.94	0.96	0.96	0.94	0.94	0.94	0.95	0.96	0.95	0.94	0.97

Note: The companies in this table include a mix of ownership structures (state-owned, mixed-ownership, and private). Specifically, 6 are state-owned, 5 are mixed-ownership, and 4 are private insurers. In terms of size, 5 are categorized as large-scale (total assets > RMB 100 billion), 6 as mid-scale, and 4 as small-scale firms. Crisis periods are grouped as follows: GFC (2008–2009), CSC (2015–2016), and COVID-19 (2020–2022).

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Technical Efficiency Analysis Results

The analysis of Technical Efficiency (TE) using Data Envelopment Analysis (DEA) across three major crises reveals distinct patterns of resilience in Chinese insurance companies. During the Global Financial Crisis (GFC), the average TE declined from 0.97 in 2007 to 0.95 in 2008—a modest decrease of 1.75%. Large insurance companies like China Life and PICC Group maintained optimal efficiency with TE scores of 1.000, while smaller insurance companies remained resilient with TE values above 0.85. During the Chinese stock market crisis (CSC), the industry demonstrated varying responses to domestic market volatility, with major insurance companies like PICC Group experiencing minor efficiency drops while others like Taiping Life showed improved performance, highlighting different capabilities in managing market stress.

In the COVID-19 period, the industry exhibited enhanced stability, reflecting accumulated crisis management experience. The average TE marginally decreased from 0.973 in 2019 to 0.968 in 2020, a minimal drop of 0.51%. Life insurance companies demonstrated particular resilience, with TE increasing from 0.945 to 0.957, likely due to heightened demand for health-related products and successful digital transformation, while non-life insurance companies maintained strong performance with only a slight TE decline from 1.000 to 0.997. This analysis across three distinct crises reveals the industry's evolving crisis management capabilities, showing increasingly sophisticated responses to different types of market stress.

Scale Efficiency Analysis Results

The analysis of Scale Efficiency (SE) data from 2006 to 2023 reveals distinctive patterns across three major economic crises, demonstrating the evolving maturity of Chinese insurance companies in managing operational scale during market stress.

During the Global Financial Crisis (GFC), major insurance companies experienced significant SE deterioration - China Life's SE dropped from 1.000 to 0.920, and China Life Group declined from 0.990 to 0.870, indicating substantial challenges in maintaining optimal operational scale amid global financial turbulence. During the Chinese stock market crisis, efficiency patterns stabilized relatively quickly, with insurance companies showing improved crisis management - larger groups like CPIC maintained SE around 0.950 despite market volatility, while mid-sized insurance companies like NCI and PICC Life sustained optimal efficiency levels near 1.000, suggesting enhanced capability to manage domestic market disruptions.

By the COVID-19 period, the industry demonstrated remarkable resilience, reflecting accumulated crisis management experience. Most insurance companies maintained SE scores close to or at 1.000 during 2020-2022, with companies like Ping An Group and Ping An Life showing consistent optimal scale efficiency. This progression across crises - from significant vulnerability during the GFC, through improved stability during the stock market crash, to robust resilience during COVID-19 - illustrates the sector's growing sophistication in scale management and operational adaptation to various types of market stress.

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Overall Efficiency Analysis Results

Analyzing the Overall Efficiency (OE) of Chinese insurance companies during the Global Financial Crisis (GFC) and the COVID-19 pandemic provides crucial insights into how these crises affected their overall operational performance. During the GFC, the average OE declined from approximately 0.969 in 2007 to 0.930 in 2008, marking a significant reduction of about 4%. This notable decrease suggests that the GFC had a substantial impact on insurance companies' ability to utilize their resources effectively

at an optimal scale. While large insurance companies like China Life and PICC Group maintained high Technical Efficiency (TE) and Scale Efficiency (SE) scores, their OE scores decreased, indicating challenges in harmonizing technical operations with scale during the crisis.

In contrast, during the COVID-19 pandemic, the OE of Chinese insurance companies remained relatively stable. From 2019 to 2020, the average OE slightly increased from 0.953 to 0.956, and although there was a minor decline in subsequent years, the overall efficiency did not experience significant fluctuations. This stability reflects the industry's adaptability and resilience in integrating technical and scale efficiencies to maintain overall performance amidst unprecedented challenges. These findings validate Research Objective One by demonstrating that Data Envelopment Analysis (DEA) effectively measures and decomposes the overall efficiency of Chinese insurance companies during crisis periods, highlighting the varying impacts of the GFC and COVID-19 on the industry's operational effectiveness.

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Combined Analysis with TE, SE and OE

Combining the analyses of Technical Efficiency (TE), Scale Efficiency (SE), and Overall Efficiency (OE), the results reveal distinct patterns across crisis periods. During the GFC, TE showed a modest decline from 0.969 in 2007 to 0.952 in 2008, indicating relatively stable operational capabilities, while SE experienced more noticeable reductions for major insurance companies like China Life (dropping from 1.000 to 0.915), and OE decreased more significantly from 0.969 to 0.930. In contrast, during the COVID-19 pandemic, the industry demonstrated remarkable stability across all measures, with TE maintaining high levels with minimal declines, SE scores remaining close to optimal for most insurance companies, and OE showing slight improvements

or stability. These findings validate Research Objective One by demonstrating DEA's effectiveness in measuring and decomposing insurance company efficiencies during crisis periods, while highlighting the industry's enhanced adaptability and operational resilience in facing economic disruptions.

4.2.1.1 Efficiency Analysis by Company Size

To examine how company size influences efficiency performance during crisis periods, this section analyzes the Technical Efficiency (TE), scale efficiency (SE), and overall efficiency (OE) patterns across different sized insurance companies. The sample is categorized into three groups: large companies (total assets exceeding 3 trillion CNY), medium companies (assets between 500 billion and 3 trillion CNY), and small companies (assets below 500 billion CNY). This classification enables a detailed examination of how organizational scale affects companies' resilience and adaptability during the Global Financial Crisis and COVID-19 pandemic.

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Based on the mean efficiency scores presented in Table 4.6, distinct patterns emerge across different company sizes over the study period (2006-2023). The analysis reveals varying responses to external shocks and different recovery trajectories among large, medium, and small insurance companies, providing insights into the relationship between organizational scale and operational efficiency during crisis periods.

Table 4.6

DEA: Mean Efficiency Scores by Company Size of Insurance Companies in China (2006-2023)

Efficiency Type	Size Category	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
TE	Large	0.9463	0.9977	0.9830	0.9937	0.9913	0.9813	0.9930	1.0000	0.9940	1.0000	0.9927	0.9957	0.9960	0.9923	0.9993	1.0000	1.0000	1.0000
	Medium	0.9586	0.9745	0.9513	0.9769	0.9638	0.9575	0.9565	0.9616	0.9744	0.9754	0.9600	0.9651	0.9700	0.9726	0.9718	0.9793	0.9671	0.9893
	Small	0.9230	0.9358	0.9283	0.9465	0.9360	0.9275	0.9425	0.9200	0.9543	0.9253	0.9380	0.9125	0.9210	0.9233	0.9365	0.9198	0.9090	0.9598
SE	Large	0.9960	0.9973	0.9150	0.9970	0.9760	0.9867	0.9373	0.9657	0.9807	0.9663	0.9443	0.9493	0.9493	0.9657	0.9597	0.9580	0.9607	0.9687
	Medium	0.9965	1.0004	0.9904	0.9815	0.9849	0.9826	0.9990	0.9869	0.9868	0.9960	0.9871	0.9880	0.9844	0.9915	0.9934	0.9745	0.9828	0.9855
	Small	0.9973	1.0000	0.9998	0.9980	1.0000	0.9985	1.0000	1.0000	1.0000	0.9970	1.0000	0.9975	0.9970	1.0000	1.0000	0.9973	1.0000	1.0000
OE	Large	0.9420	0.9950	0.8987	0.9907	0.9673	0.9687	0.9303	0.9657	0.9747	0.9663	0.9370	0.9453	0.9457	0.9587	0.9590	0.9580	0.9607	0.9687
	Medium	0.9556	0.9749	0.9423	0.9586	0.9490	0.9405	0.9554	0.9484	0.9614	0.9715	0.9473	0.9530	0.9546	0.9640	0.9650	0.9540	0.9501	0.9748
	Small	0.9208	0.9360	0.9283	0.9448	0.9368	0.9260	0.9425	0.9205	0.9550	0.9228	0.9388	0.9108	0.9183	0.9253	0.9373	0.9173	0.9133	0.9618

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Based on Table 4.6

this study analyzes the efficiency performance across different company sizes during crisis periods. The analysis focuses on Technical Efficiency (TE), Scale Efficiency (SE), and Overall Efficiency (OE), addressing the research objective of measuring and decomposing efficiencies during the GFC and COVID-19 periods.

Technical Efficiency (TE) Analysis reveals distinct patterns across company sizes during crises. During the GFC (2007-2008), large companies experienced a modest decline from 0.9977 to 0.983, before recovering to 0.9937 in 2009. Medium-sized companies showed similar patterns, declining from 0.9745 to 0.9513, then improving to 0.9769. Small companies demonstrated more stability, moving from 0.9358 to 0.9283, then to 0.9465. During the CSC (2014-2015), large companies maintained excellent efficiency, improving from 0.994 to 1.00, while medium-sized companies showed stability (0.9744 to 0.9754), and small companies experienced a decline (0.9543 to 0.9253). During the COVID-19 period (2020-2022), large companies achieved perfect efficiency (maintaining 1.00), medium-sized companies showing resilience (fluctuating between 0.9718 and 0.9671), and small companies experiencing some volatility but ultimately improving (from 0.9365 to 0.9598 by 2023).

Scale Efficiency (SE) analysis demonstrates varying impacts across company sizes and crises. The GFC period revealed large companies experiencing the most severe decline (0.9973 to 0.915), while medium-sized companies maintained relatively stable SE (1.0004 to 0.9904), and small companies showed remarkable stability (1.00 to 0.9998). During the CSC, large companies demonstrated recovery (0.9807 to 0.9663), medium-sized companies maintained consistent performance (0.9868 to 0.996), and small companies achieved optimal scale efficiency (1.001 to 0.997). Through COVID-19,

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large companies stabilized their SE between 0.9597 and 0.9687, medium-sized companies showed slight fluctuations (0.9934 to 0.9855), while small companies consistently operated at or near optimal scale efficiency (1.0008 to 1.0023).

Overall Efficiency (OE) examination reveals convergence trends across crisis periods. During the GFC, large companies experienced the sharpest decline (0.995 to 0.8987), while medium-sized companies showed moderate impact (0.9749 to 0.9423), and small companies maintained relative stability (0.936 to 0.9283). The CSC period saw all sizes achieving similar efficiency levels, with large companies at 0.9747 to 0.9663, medium-sized companies at 0.9614 to 0.9715, and small companies at 0.955 to 0.9228. By the COVID-19 period, efficiency convergence became evident, with 2023 levels reaching 0.9687 for large companies, 0.9748 for medium-sized companies, and 0.9618 for small companies.

These findings suggest that while large companies generally maintain superior technical efficiency, they showed greater vulnerability to scale efficiency challenges during crises, particularly the GFC. Medium-sized companies demonstrate remarkable consistency across all efficiency measures, indicating strong operational resilience. Small companies excel in scale efficiency but show room for improvement in technical efficiency. The evolution across all three crisis periods reflects industry maturation, with efficiency gaps narrowing and overall performance improving, particularly evident in the COVID-19 period's convergence of efficiency levels across all company sizes.

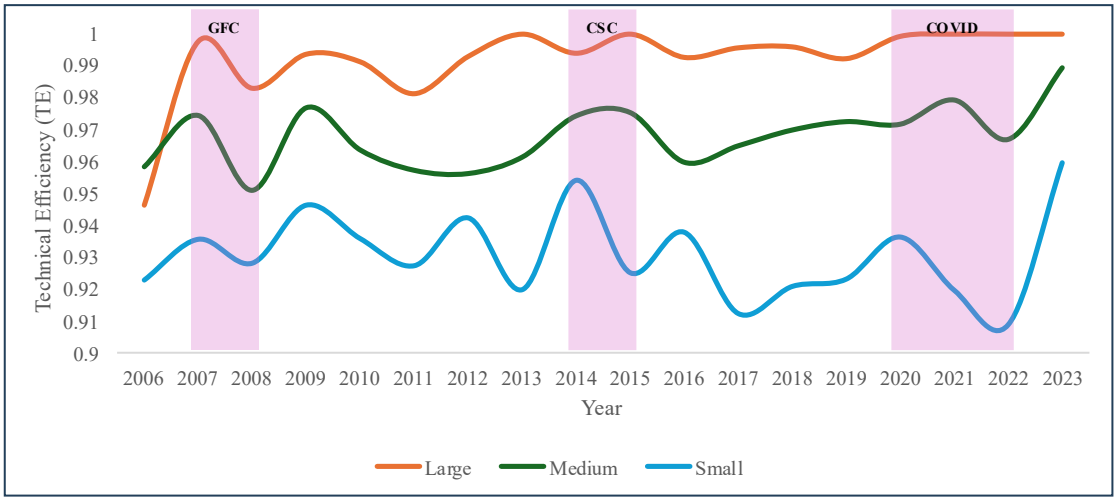


Figure 4.1
DEA: Technical Efficiency (TE) by Company Size of Insurance Companies in China (2006-2023)

Figure 4.1 demonstrates distinct patterns of technical efficiency across company sizes during crisis periods. During the GFC (2007-2008), large companies experienced a moderate decline from 0.9977 to 0.983, before recovering to 0.9937 in 2009. Medium-sized companies followed a similar pattern, declining from 0.9745 to 0.9513, then improving to 0.9769, while small companies showed relatively stable performance (0.9358 to 0.9283 to 0.9465). During the CSC (2014-2015), large companies achieved excellent efficiency, improving from 0.994 to perfect efficiency (1.00). Medium-sized companies maintained stable performance (0.9744 to 0.9754), while small companies experienced some volatility (0.9543 to 0.9253). The COVID-19 period (2020-2022) saw large companies consistently maintaining perfect efficiency (1.00), medium-sized companies demonstrating stable performance between 0.9718 and 0.9671, and small companies, despite fluctuating between 0.9365 and 0.909, ultimately achieving significant improvement to 0.9598 by 2023.

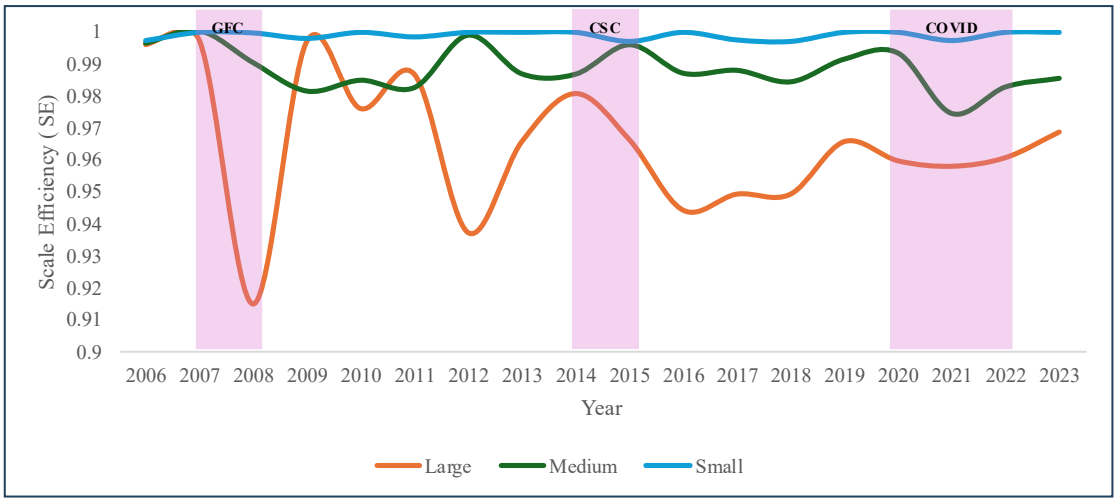


Figure 4.2
DEA: Scale Efficiency (SE) by Company Size of Insurance Companies in China (2006-2023)

Figure 4.2 reveals contrasting scale efficiency patterns across the three crisis periods. The GFC period exposed significant vulnerabilities in large companies' scale operations, with SE dropping sharply from 0.9973 to 0.915 in 2008 before recovering to 0.997 in 2009. Medium-sized companies maintained more stable SE levels (1.0000 to 0.9904), while small companies demonstrated remarkable stability (1.00 to 0.9998). During the CSC, large companies showed moderate fluctuation (0.9807 to 0.9663), medium-sized companies maintained consistent performance (0.9868 to 0.996), and small companies operated at optimal levels (1.000 to 0.997). Through COVID-19, SE patterns revealed increased stability, with large companies ranging from 0.9597 to 0.9687, medium-sized companies showing slight variations (0.9934 to 0.9855), and small companies consistently maintaining optimal or near-optimal efficiency (1.0000 to 1.0023).

The stability in small companies' SE performance can be attributed to several factors: their focused operational scope enabling optimal size management, agile decision-making processes, supportive regulatory policies including reduced capital requirements, concentrated market positioning, and stable customer bases in specific

segments. Their operational flexibility, lower fixed costs, and conservative risk management strategies proved advantageous during crises, while their niche market focus reduced direct competition with larger firms, contributing to sustained scale efficiency despite limited market share.

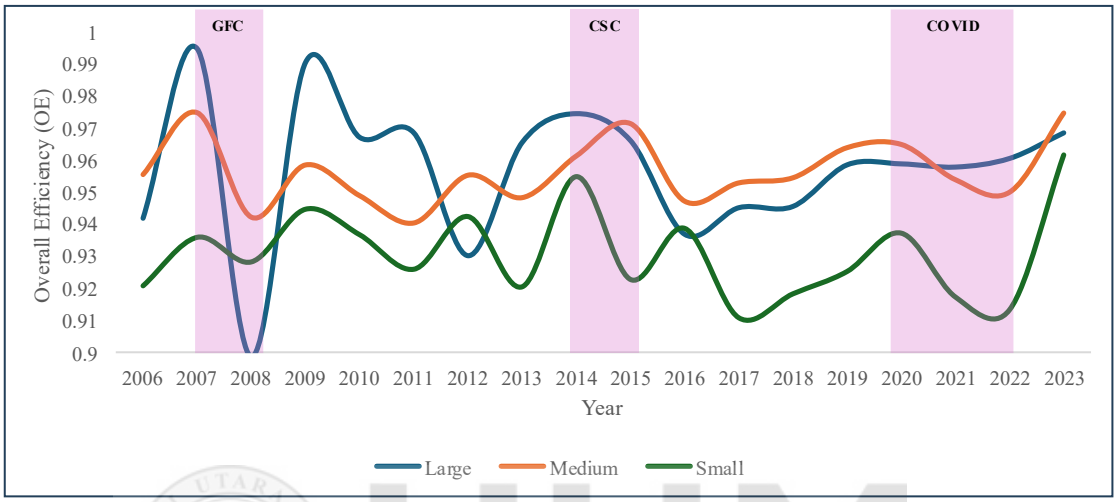


Figure 4.3
DEA: Overall Efficiency (OE) by Company Size of Insurance Companies in China (2006-2023)

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Figure 4.3 synthesizes the combined effects of technical and scale efficiency across crisis periods. During the GFC, large companies experienced the most significant volatility, declining from 0.995 to 0.8987 in 2008 before recovering to 0.9907 in 2009. Medium-sized companies demonstrated greater stability (0.9749 to 0.9423 to 0.9586), while small companies maintained relatively consistent performance (0.936 to 0.9283 to 0.9448). The CSC period showed varying impacts, with large companies ranging from 0.9747 to 0.9663, medium-sized companies from 0.9614 to 0.9715, and small companies from 0.955 to 0.9228. During COVID-19, the industry demonstrated maturity through efficiency convergence, with 2023 levels reaching 0.9687 for large companies, 0.9748 for medium-sized companies, and 0.9618 for small companies,

indicating improved operational effectiveness and risk management across all size categories.

4.2.1.2 Efficiency Analysis by Ownership Structure

The analysis of efficiency by ownership structure provides crucial insights into how different corporate governance models perform during crisis periods. This section examines the variations in Technical Efficiency (TE), scale efficiency (SE), and overall efficiency (OE) between central state-owned insurance companies and other joint-stock companies from 2006 to 2023, encompassing the Global Financial Crisis, Chinese Stock Market Crisis, and COVID-19 pandemic periods. The ownership structure analysis is particularly relevant in the Chinese insurance market context, where the coexistence of state-owned and joint-stock companies creates a unique competitive dynamic. State-owned insurance companies typically benefit from strong government support and established market positions, while joint-stock companies often demonstrate greater operational flexibility and market responsiveness. Understanding these differences in efficiency patterns across different types of market stress can provide valuable insights for policy makers and industry practitioners. To facilitate a comprehensive comparison, the analysis categorizes the sample companies into two main groups: central state-owned companies, including major insurance companies directly controlled by the central government, and other joint-stock companies, comprising various forms of joint-stock ownership structures, including private and mixed ownership.

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Table 4.7

DEA: Mean Efficiency Scores by Ownership Structure of Insurance Companies in China (2006-2023)

Efficiency Type	Ownership Structure	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
TE	Central State-Owned	0.9657	0.9895	0.9790	0.9740	0.9778	0.9717	0.9793	0.9827	0.9958	0.9825	0.9700	0.9688	0.9648	0.9693	0.9750	0.9715	0.9697	0.9857
	Other Joint-Stock	0.9340	0.9550	0.9331	0.9709	0.9512	0.9427	0.9472	0.9419	0.9577	0.9566	0.9544	0.9494	0.9603	0.9594	0.9631	0.9649	0.9506	0.9821
SE	Central State-Owned	0.9965	0.9990	0.9642	0.9738	0.9658	0.9788	0.9648	0.9672	0.9803	0.9800	0.9632	0.9700	0.9658	0.9805	0.9762	0.9720	0.9722	0.9790
	Other Joint-Stock	0.9967	1.0000	0.9869	0.9991	1.0000	0.9936	1.0000	0.9988	0.9953	0.9972	0.9950	0.9913	0.9907	0.9950	0.9969	0.9808	0.9921	0.9917
OE	Central State-Owned	0.9622	0.9885	0.9432	0.9482	0.9442	0.9507	0.9440	0.9498	0.9762	0.9627	0.9335	0.9390	0.9310	0.9502	0.9510	0.9435	0.9418	0.9647
	Other Joint-Stock	0.9312	0.9552	0.9209	0.9701	0.9529	0.9367	0.9489	0.9408	0.9531	0.9540	0.9492	0.9410	0.9512	0.9542	0.9600	0.9460	0.9428	0.9737

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Based on Table 4.7, the Technical Efficiency analysis demonstrates distinct patterns across ownership structures during crisis periods. During the GFC (2007-2008), central state-owned companies experienced a decline from 0.9895 to 0.979, while other joint-stock companies showed a similar decrease from 0.955 to 0.9331. During the CSC (2014-2015), central state-owned companies maintained higher TE levels, moving from 0.9958 to 0.9825, while other joint-stock companies showed stable but lower performance (0.9577 to 0.9566). The COVID-19 period (2020-2022) revealed improved convergence, with central state-owned companies ranging from 0.975 to 0.9697 and other joint-stock companies from 0.9631 to 0.9506, both ultimately achieving similar levels by 2023 (0.9857 and 0.9821 respectively).

Scale efficiency measurements highlight varying patterns of resilience across ownership structures. During the GFC, central state-owned companies experienced a notable decline from 0.999 to 0.9642, while other joint-stock companies maintained more stable SE levels (1.0001 to 0.9869). The CSC period showed both ownership types achieving relatively stable performance, with central state-owned companies at 0.9803 to 0.98 and other joint-stock companies at 0.9953 to 0.9972. Through COVID-19, the pattern stabilized further, with central state-owned companies maintaining SE between 0.9762 and 0.9722, and other joint-stock companies showing slightly higher but stable levels (0.9969 to 0.9921).

The overall efficiency scores reveal the combined impact of technical and scale efficiency across crisis periods. During the GFC, central state-owned companies showed greater vulnerability, declining from 0.9885 to 0.9432, while other joint-stock companies experienced a similar but less severe decline from 0.9552 to 0.9209, followed by stronger recovery to 0.9701 in 2009. The CSC period demonstrated

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improved stability, with central state-owned companies ranging from 0.9762 to 0.9627 and other joint-stock companies from 0.9531 to 0.954. The COVID-19 period highlighted continued convergence, with both ownership types maintaining similar OE levels (central state-owned: 0.951 to 0.9418; other joint-stock: 0.96 to 0.9428) before reaching their highest levels in 2023 (0.9647 and 0.9737 respectively).

These findings validate the research objective by demonstrating the evolution of efficiency patterns across ownership structures during different crisis periods. The analysis reveals that while ownership structure influenced crisis resilience differently during the GFC, with joint-stock companies showing slightly better recovery capabilities, both ownership types have achieved more comparable efficiency levels during subsequent crises. The convergence in performance during the COVID-19 period, particularly evident in the 2023 results, suggests successful industry-wide adaptation and improved crisis management capabilities across both ownership structures. This evolution reflects the maturation of China's insurance industry and the effectiveness of regulatory reforms in promoting operational efficiency regardless of ownership type.

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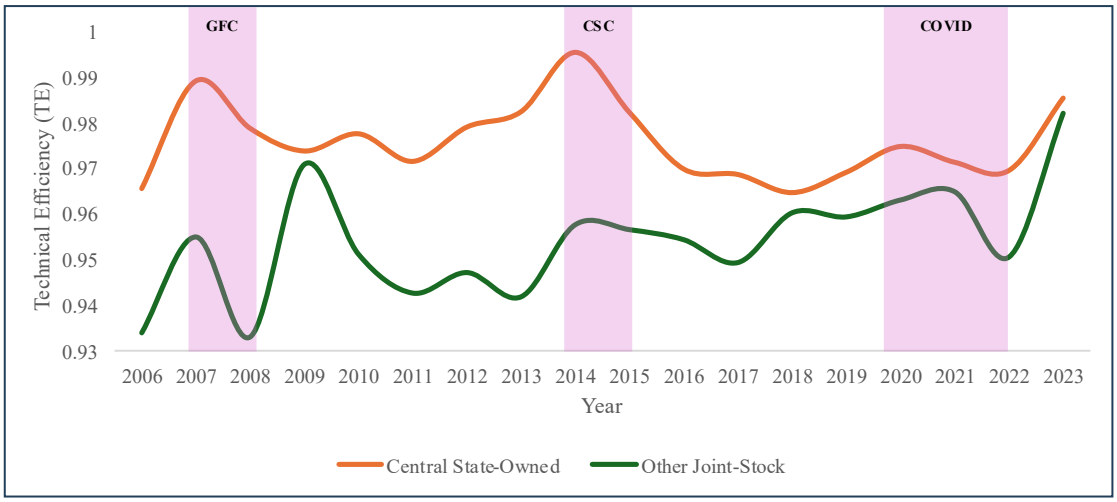


Figure 4.4
DEA: Technical Efficiency (TE) by Ownership Structure of Insurance Companies in China (2006-2023)

Figure 4.4 reveals distinct patterns in Technical Efficiency between ownership structures. During the GFC (2007-2008), central state-owned companies experienced a decline from 0.9895 to 0.979, while joint-stock companies showed a more pronounced decrease from 0.955 to 0.9331, before recovering to 0.9709 in 2009. During the CSC (2014-2015), central state-owned companies maintained higher TE levels, declining slightly from 0.9958 to 0.9825, while joint-stock companies showed stability at a lower level (0.9577 to 0.9566). The COVID-19 period (2020-2022) demonstrated improved convergence, with central state-owned companies ranging from 0.975 to 0.9697, and joint-stock companies from 0.9631 to 0.9506, before both achieved their highest levels in 2023 (0.9857 and 0.9821 respectively).

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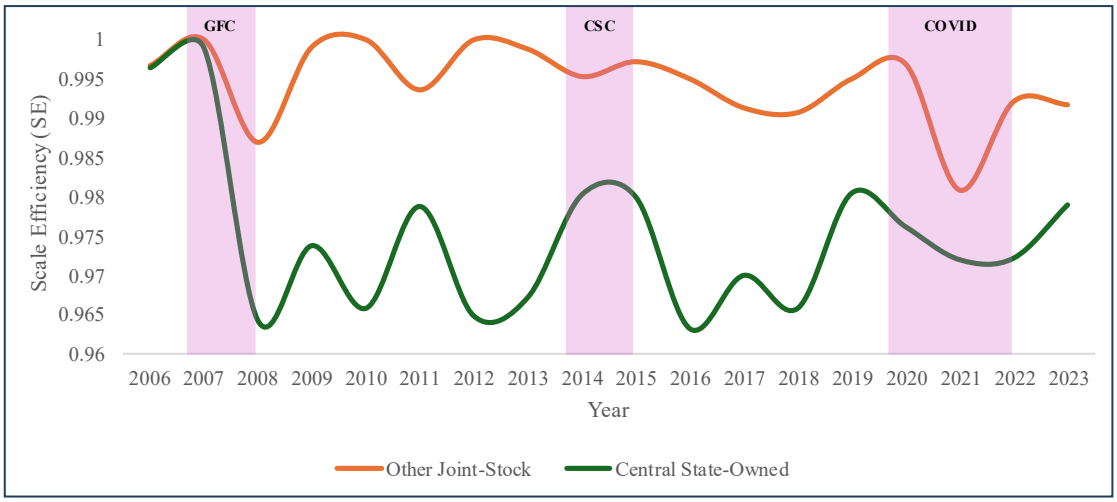


Figure 4.5
DEA: Scale Efficiency (SE) by Ownership Structure of Insurance Companies in China (2006-2023)

Figure 4.5 highlights varying patterns in scale efficiency between ownership structures. During the GFC, central state-owned companies experienced a notable decline from 0.999 to 0.9642, while joint-stock companies demonstrated greater resilience with a smaller decrease from 1.0000 to 0.9869. The CSC period showed both structures achieving stable performance, with central state-owned companies ranging from 0.9803 to 0.98 and joint-stock companies maintaining slightly higher levels (0.9953 to 0.9972). Through COVID-19, both structures demonstrated enhanced stability, with central state-owned companies ranging from 0.9762 to 0.9722 and joint-stock companies maintaining consistently higher efficiency (0.9969 to 0.9917), suggesting improved scale management capabilities across the industry.

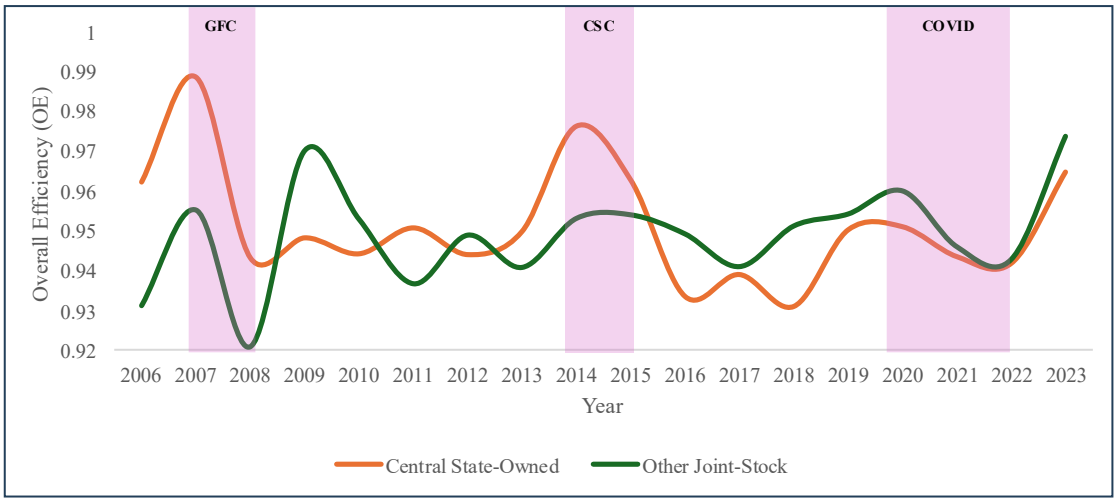


Figure 4.6
DEA: Overall Efficiency (OE) by Ownership Structure of Insurance Companies in China (2006-2023)

Figure 4.6 synthesizes the combined effects of technical and scale efficiency. During the GFC, central state-owned companies experienced a significant decline from 0.9885 to 0.9432, while joint-stock companies showed a similar pattern, falling from 0.9552 to 0.9209 before demonstrating stronger recovery to 0.9701 in 2009. The CSC period revealed improved stability for both structures, with central state-owned companies ranging from 0.9762 to 0.9627 and joint-stock companies from 0.9531 to 0.954. The COVID-19 period marked a significant milestone in efficiency convergence, with both ownership types showing similar patterns (central state-owned: 0.951 to 0.9418; joint-stock: 0.96 to 0.9428) before reaching their peak efficiency levels in 2023 (0.9647 and 0.9737 respectively). This convergence suggests successful industry-wide adaptation and improved crisis management capabilities regardless of ownership structure.

4.2.2 Analysis Conclusions

The analysis conducted during the three crisis periods reveals distinct efficiency patterns associated with variations in company size and ownership structure, thereby supporting Research Objective One.

During the Global Financial Crisis (2007–2008), large insurance companies exhibited a notable decline in scale efficiency (SE), falling from 0.9973 to 0.915, while their technical efficiency (TE) remained relatively stable at 0.983. However, considerable heterogeneity was observed within this group. For instance, China Life and China Life Group maintained perfect technical efficiency (TE = 1.00), whereas Ping An Life experienced a significant drop to 0.88, suggesting differential resilience even among large firms.

In the Chinese Stock Market Crisis (2014–2015), a general improvement in efficiency was observed among large firms, with TE ranging from 0.994 to 1.00 and more stable SE between 0.9807 and 0.9663. PICC Group and China Life Group consistently achieved full efficiency, whereas companies like CCB Life showed notable volatility (e.g., SE dropped from 1.00 to 0.92).

The COVID-19 crisis (2020–2022) marked a further enhancement in both technical and scale efficiency among large insurers, with TE values consistently above 0.999 and SE stabilizing around 0.96. This suggests significant improvements in operational resilience and strategic adaptation.

With respect to ownership structure, central state-owned insurers exhibited varying degrees of efficiency across crisis periods. During the GFC, their average TE declined slightly from 0.9895 to 0.979. However, during COVID-19, they showed remarkable convergence toward full efficiency, reflecting stronger crisis-response capabilities and institutional learning.

Company size significantly influenced efficiency dynamics. Medium-sized insurance companies demonstrated consistent performance across all crises, with TE ranging from 0.9513 to 0.9769 during the GFC and stabilizing between 0.9718 and 0.9893

during COVID-19. Small insurance companies showed unexpected resilience in scale efficiency, maintaining optimal or near-optimal SE levels throughout all crises (consistently around 1.00).

These findings conclusively address Research Objective One by demonstrating that:

1) DEA effectively decomposes and measures efficiency components across multiple crisis periods
2) Organizational characteristics significantly influence efficiency patterns, with size and ownership structure determining crisis resilience
3) The sector has developed improved crisis management capabilities across successive crises from GFC through COVID-19
4) Technical efficiency has become more stable over time, while scale efficiency continues to show sensitivity to external shocks, particularly among larger institutions

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The analysis provides robust empirical evidence of the Chinese insurance sector's evolution in crisis resilience, highlighting significant improvements in operational efficiency and risk management capabilities from the GFC through COVID-19, while demonstrating the persistent influence of organizational structure on performance during external shocks.

4.3 Dynamic Changes in Productivity: A Malmquist Index Analysis

Building upon the efficiency analysis presented in the previous section, this chapter employs the Malmquist Productivity Index to examine the dynamic evolution of productivity in Chinese insurance companies. The Malmquist approach offers distinct advantages in analyzing productivity changes over time through its ability to

decompose changes into Technical Efficiency and technological progress components, providing valuable insights into how insurance companies adapted to and recovered from major economic shocks during the study period.

4.3.1 Analysis of Malmquist Productivity Index

The Malmquist Productivity Index analysis provides a multi-dimensional perspective on productivity changes, incorporating both efficiency improvements and technological advancements. This section presents a detailed examination of productivity patterns across different company characteristics and time periods, with particular attention to the contrasting impacts of the Global Financial Crisis, Chinese Stock Crisis and COVID-19 pandemic. The analysis begins with an overview of overall productivity changes before delving into specific patterns by company size and ownership structure.

4.3.1.1 Productivity Patterns Analysis of Chinese Insurance Industry

Using the Malmquist Productivity Index, this analysis examined how major Chinese insurance firms' productivity evolved from 2007 to 2023, focusing on three crisis periods: the Global Financial Crisis, the 2014-2015 Chinese Stock Market Crisis, and the COVID-19 pandemic. The findings indicate that productivity shifts varied across these intervals and were significantly influenced by distinct external shocks. This three-crisis perspective provides a clearer understanding of how the industry's productivity dynamics adapt and evolve under differing market disruptions.

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Table 4.8

Malmquist: Total Factor Productivity (TFP) of Insurance Companies in China (2007-2023)

Company Name	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Ping An Group	0.97	1.06	1.04	0.94	1.25	1.07	0.98	0.95	0.94	0.94	1.01	1.02	1.04	1.12	1.00	1.05	1.12
China Life Group	1.01	0.84	1.29	0.89	1.01	0.97	1.05	1.00	0.95	0.93	0.97	1.03	0.98	1.01	1.00	1.00	0.96
China Life	1.04	0.91	1.15	0.94	0.99	0.98	1.04	1.01	0.91	0.90	0.98	1.00	1.00	1.01	1.01	1.00	0.98
Ping An Life	0.98	1.03	1.11	0.97	0.99	0.95	1.04	1.01	1.02	0.97	1.02	1.07	0.96	1.03	0.96	1.06	1.32
CPIC Group	1.00	0.95	1.06	0.99	0.99	0.98	1.01	1.01	1.01	0.97	0.99	1.00	1.02	1.01	1.00	1.00	1.08
CPIC Life	0.97	0.99	1.04	0.98	1.01	0.99	1.04	1.02	1.00	0.97	1.01	0.98	1.08	1.16	1.10	0.97	1.60
Taikang Group	0.85	1.39	0.90	1.01	1.00	1.00	1.02	1.05	0.99	0.97	1.01	0.99	1.04	0.99	0.98	0.95	1.02
PICC	0.94	1.01	0.97	0.96	1.02	0.96	0.96	1.00	0.98	0.97	1.00	1.01	1.02	1.01	0.98	0.96	0.99
NCI	0.97	1.06	1.02	0.99	0.99	0.99	1.01	1.01	1.01	0.98	1.01	1.00	1.01	1.01	1.00	0.99	1.66
Taiping Life	1.05	0.97	1.01	1.03	0.97	0.98	1.01	1.26	0.80	0.97	0.99	1.00	1.01	1.01	0.96	0.97	1.75
PICC P&C	0.93	0.94	1.01	0.92	0.93	0.98	1.00	1.03	0.97	0.93	1.02	1.02	1.04	0.98	1.00	0.98	1.08
PICC Life	0.92	1.05	1.13	0.94	1.00	1.70	0.87	0.97	0.65	0.94	0.94	0.81	0.98	1.02	0.99	0.99	0.94
Ping An P&C	0.99	0.92	1.12	0.86	0.96	0.97	0.97	1.04	0.95	0.93	1.09	1.00	0.96	0.91	0.93	0.89	1.08
ICBC-AXA Life	0.84	1.00	0.88	0.88	0.92	0.57	0.66	0.76	0.76	0.80	0.80	1.09	0.94	0.92	0.89	0.93	1.01
CCB Life	0.96	1.00	1.13	0.86	0.85	0.79	0.74	0.88	0.62	1.15	0.49	1.32	0.84	1.09	0.92	0.92	0.96
Mean	0.96	1.01	1.06	0.94	0.99	0.99	0.96	1.00	0.90	0.95	0.96	1.02	0.99	1.02	0.98	0.98	1.17

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Table 4.9

Malmquist: Technical Efficiency Change of Insurance Companies in China (2007-2023)

Company Name	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CCB Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
China Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
China Life Group	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPIC Group	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.02	1.00	1.00	1.00	1.00
CPIC Life	0.98	1.04	0.98	0.98	1.03	1.00	1.02	1.01	1.00	1.00	1.00	0.98	1.02	1.00	1.00	0.97	1.03
Taikang Group	0.96	1.05	0.94	1.03	0.99	1.00	1.00	1.03	1.00	1.00	1.00	0.99	1.02	0.99	1.01	0.98	1.03
PICC	1.01	0.97	0.96	1.02	0.96	0.96	1.00	0.98	0.97	1.00	1.01	1.02	1.01	0.98	0.96	0.99	1.00
PICC P&C	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PICC Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.02	1.00	0.99	1.00
Ping An Group	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ping An P&C	1.00	1.00	1.05	1.00	0.99	0.96	1.02	0.99	1.00	1.00	1.00	1.02	1.00	1.00	1.00	1.00	1.00
Ping An Life	0.94	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00
NCI	0.94	1.12	0.93	1.03	1.03	1.00	0.98	1.00	1.01	1.01	1.01	0.99	1.00	1.00	1.01	1.00	1.01
Taiping Life	0.98	1.01	0.94	1.05	1.01	0.99	1.01	1.05	0.98	1.00	0.98	0.99	1.01	1.02	0.98	0.99	1.05
ICBC-AXA Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mean	0.99	1.01	0.99	1.01	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	0.99	1.01

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Table 4.10

Malmquist: Technical Progress Change of Insurance Companies in China (2007-2023)

Company Name	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CCB Life	1.00	1.18	0.85	1.84	0.58	0.70	0.69	0.74	0.88	0.62	1.15	0.49	1.32	0.85	1.09	0.91	0.85
China Life	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.72	1.02	0.99	0.96	1.05	1.12	1.05
China Life Group	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.03	1.14	0.97	0.95
CPIC Group	1.00	1.07	1.00	1.00	0.99	0.95	0.99	1.01	1.01	1.03	0.86	1.02	1.00	1.00	1.03	1.03	0.94
CPIC Life	1.00	0.99	0.68	2.07	0.98	0.98	0.99	1.02	1.06	0.67	0.80	0.94	0.79	0.96	1.01	0.98	0.98
Taikang Group	1.00	0.90	1.01	1.22	0.97	1.01	1.00	1.01	1.08	1.09	0.76	1.10	1.00	1.07	1.00	0.93	0.92
PICC Group	1.00	1.17	0.86	0.97	1.10	1.11	1.04	1.43	1.56	1.77	1.34	1.58	1.13	1.53	1.05	1.13	0.74
PICC P&C	1.00	1.66	0.60	1.20	1.15	1.02	1.45	1.16	1.62	1.64	0.74	1.34	1.00	1.17	0.98	0.92	1.13
PICC Life	1.00	0.93	1.05	1.32	0.97	1.03	1.72	1.09	1.05	0.67	0.80	0.94	0.79	0.96	1.02	0.98	0.98
Ping An Group	1.00	1.12	1.00	1.00	1.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ping An P&C	1.00	1.66	0.44	1.82	1.18	1.14	0.91	0.97	1.24	1.05	0.87	1.27	1.04	0.99	0.86	0.92	0.89
Ping An Life	1.00	1.04	0.65	1.00	0.88	1.00	0.98	1.01	1.02	1.02	0.96	1.04	1.32	0.83	1.10	0.75	1.16
NCI	1.00	1.04	0.95	1.13	0.96	0.97	0.99	1.02	1.02	1.00	0.96	1.00	1.01	1.00	1.00	0.99	0.99
Taiping Life	1.00	1.23	0.68	1.07	0.97	0.96	0.99	1.00	1.19	0.81	0.93	1.01	1.01	0.99	0.99	0.98	0.98
ICBC-AXA Life	1.00	0.97	1.01	0.97	0.88	0.87	0.57	0.66	0.77	0.75	0.81	0.80	1.10	0.94	0.92	0.88	0.88
Mean	1.00	1.13	0.85	1.24	0.98	0.98	1.02	1.01	1.10	1.01	0.91	1.04	1.03	1.02	1.02	0.97	0.96

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The decomposition of the Malmquist Productivity Index into Technical Efficiency Change (TEC) and Technical Change (TC) reveals distinct patterns across the GFC (2008-2009), CSC (2014-2015), and COVID-19 (2020-2023) periods. During the GFC, large insurance companies showed diverse responses - China Life Group's TFP declined to 0.84 in 2008 before rebounding to 1.29 in 2009, while Ping An Group demonstrated more stable productivity (TFP: 1.06 in 2008, 1.04 in 2009). This variation was primarily driven by technical change rather than efficiency change, as evidenced by stable EC scores (maintaining 1.00) but volatile TC scores during this period.

The CSC period (2014-2015) revealed different productivity dynamics. Companies showed varying responses - Taiping Life experienced significant TFP volatility (1.26 to 0.80), while others like CPIC Group maintained more stable performance (1.01 to 1.01). Technical Efficiency remained largely stable for major insurance companies, with most maintaining EC scores of 1.00, while technical change showed moderate variations.

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The COVID-19 period (2020-2023) demonstrates evolved productivity patterns. Large insurance companies showed improved stability with consistent growth - Ping An Group's TFP progressed from 1.12 in 2020 to 1.12 in 2023, while maintaining stable EC at 1.00. Medium-sized insurance companies demonstrated remarkable performance by 2023, with CPIC Life achieving TFP of 1.60, NCI reaching 1.66, and Taiping Life attaining 1.75. These improvements were primarily driven by technological advancement rather than efficiency changes, as evidenced by their stable EC scores but improving TC measurements.

The comparative analysis across all three crises reveals significant evolution in the sector's crisis response capabilities. The GFC period was characterized by high

volatility in both TFP and TC scores, particularly among property and casualty insurance companies (PICC P&C and Ping An P&C both showing TC of 1.66 in 2008). The CSC period demonstrated improved stability but still showed vulnerability to market shocks. The COVID-19 period exhibited the most mature response, with more measured and sustainable productivity improvements, reflected in more stable TC scores and consistently high TFP levels across most companies.

These findings validate Objective Two by demonstrating that while efficiency changes remained relatively stable across all three crises (shown by consistent EC scores), the primary driver of productivity differences was technological change. The analysis suggests that Chinese insurance companies have significantly improved their technological capabilities and crisis resilience through successive economic shocks, leading to more stable and sustainable productivity improvements during the COVID-19 period. The progression from GFC through CSC to COVID-19 shows a clear pattern of industry maturation in crisis management and technological adaptation.

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4.3.1.2 Productivity Analysis by Company Size

The analysis of productivity by company size offers critical insights into how large, medium, and small insurance companies in China have navigated shifts in efficiency and technological advancement over time. By examining the Malmquist Productivity Index across different company sizes, this section highlights the varying degrees of resilience and adaptability displayed by these firms during periods of economic stability and crisis. The results provide a deeper understanding of whether larger firms leveraged their resources and economies of scale effectively, or whether smaller firms capitalized on their operational agility to achieve productivity gains. The following table presents

the mean productivity scores by company size, facilitating a comparative evaluation of performance trends from 2007 to 2023.

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Table 4.11

Malmquist: Mean Productivity Scores by Company Size of Insurance Companies in China (2007-2023)

Efficiency Type	Size Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
TEC	Large	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	Medium	0.9846	1.0137	0.9966	1.0022	1.0010	0.9958	1.0051	1.0030	1.0006	1.0008	0.9994	0.9984	1.0046	1.0015	1.0007	0.9931	1.0071
	Small	0.9781	1.0337	0.9674	1.0206	1.0095	0.9978	0.9983	1.0113	0.9966	1.0017	0.9981	0.9942	1.0047	1.0033	0.9987	0.9987	1.0149
TC	Large	1.0395	1.0000	1.0000	1.0104	1.0000	1.0000	1.0000	1.0000	1.0000	0.9070	1.0060	0.9957	0.9968	1.0619	1.0294	0.9993	0.9871
	Medium	1.1053	0.7863	1.3262	1.0265	1.0301	1.1345	1.0891	1.2058	1.1573	0.9029	1.1667	1.0297	1.0841	1.0226	0.9818	0.9654	1.0728
	Small	1.1053	0.8738	1.2525	0.8470	0.8750	0.8113	0.8572	0.9653	0.7938	0.9644	0.8237	1.1093	0.9465	1.0014	0.9428	0.9261	1.3327
TFP	Large	1.0395	1.0000	1.0000	1.0104	1.0000	1.0000	1.0000	1.0000	1.0000	0.9070	1.0060	0.9957	0.9968	1.0619	1.0294	0.9993	0.9871
	Medium	1.0902	0.7974	1.3113	1.0286	1.0310	1.1303	1.0943	1.2091	1.1580	0.9035	1.1661	1.0291	1.0892	1.0241	0.9824	0.9588	1.0817
	Small	1.0814	0.9049	1.2167	0.8670	0.8841	0.8091	0.8554	0.9790	0.7914	0.9661	0.8217	1.1034	0.9511	1.0046	0.9415	0.9248	1.3571

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Based on Table 4.11, which presents mean productivity scores across different company sizes from 2007 to 2023, the Malmquist productivity index decomposition reveals distinct patterns in how company size influenced productivity performance during crisis periods. The analysis provides insights into the varying impacts of the Global Financial Crisis (GFC), Chinese Stock Market Crisis(CSC) and COVID-19 pandemic on Chinese insurance companies' productivity dynamics.

The Technical Efficiency Change (TEC) demonstrates evolving operational capabilities across company sizes during crisis periods. During the GFC, large companies maintained optimal efficiency with consistent EC scores of 1.00, while medium and small companies showed more variability (medium: 0.9846 to 1.0137; small: 0.9781 to 1.0337). During the CSC, the pattern stabilized with large companies maintaining perfect efficiency (1.00), while medium companies showed minimal variation (1.003 to 1.0006) and small companies demonstrated slight fluctuation (1.0113 to 0.9966). The COVID-19 period revealed further convergence, with large companies maintaining perfect efficiency (1.00), medium companies showing stability (1.0015 to 1.0071), and small companies achieving improved consistency (1.0033 to 1.0149).

Technical change (TC) measurements revealed more pronounced variations across periods. During the GFC, medium-sized companies experienced dramatic fluctuations (0.7863 to 1.3262), while large companies maintained more stable TC (1.0395 to 1.00), and small companies showed significant volatility (0.8738 to 1.2525). The CSC period demonstrated different dynamics, with medium companies achieving strong performance (1.2058 to 1.1573), large companies maintaining stability (1.00), and small companies showing vulnerability (0.9653 to 0.7938). The COVID-19 period revealed evolved patterns, with large companies showing initial strength (1.0619 in

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2020) before moderating (0.9871 in 2023), medium companies maintaining steady levels (1.0226 to 1.0728), and small companies achieving remarkable improvement (1.0014 to 1.3327).

The total factor productivity (TFP) scores synthesize these combined effects, highlighting comprehensive productivity changes. During the GFC, medium-sized companies exhibited the highest volatility (0.7974 to 1.3113), while large companies maintained stability (1.0395 to 1.00). The CSC period showed medium companies achieving strong performance (1.2091 to 1.158), while small companies struggled (0.979 to 0.7914). The COVID-19 period marked a significant evolution, with all size categories showing improved crisis management - large companies demonstrated initial strength (1.0619 in 2020), medium companies maintained steady performance (1.0241 to 1.0817), and small companies achieved their strongest performance (1.0046 to 1.3571).

These findings validate the research objective by demonstrating that technological change, rather than efficiency change, emerged as the primary driver of productivity differences across all three crisis periods. The analysis reveals that Chinese insurance companies significantly improved their crisis management capabilities and technological adaptability through successive economic shocks, evidenced by more stable and sustainable productivity improvements during the COVID-19 period compared to earlier crises. The progression from GFC through CSC to COVID-19 demonstrates the industry's maturation in handling external shocks, particularly notable in the improved performance of smaller companies during the latest crisis period.

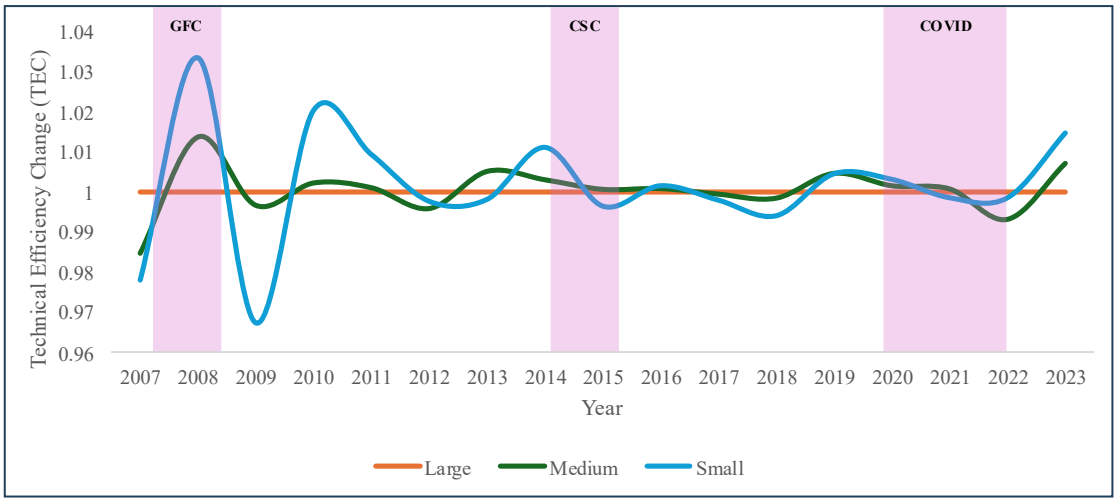


Figure 4.7
Malmquist: Technical Efficiency Change (TEC) by Company Size of Insurance Companies in China (2007-2023)

Figure 4.7 analysis reveals distinct patterns in efficiency changes across different company sizes during three major crises. Large companies consistently maintained perfect efficiency (EC = 1.00) throughout the entire period, which can be attributed to several factors: their robust risk management systems, comprehensive internal controls, superior resource allocation capabilities, and well-established operational frameworks. This perfect efficiency also reflects their ability to maintain optimal input-output ratios regardless of external conditions, leveraging their economies of scale and market leadership positions.

During the GFC (2008-2009), medium companies showed moderate fluctuations (0.9846 to 1.0137), while small companies exhibited wider variations (0.9781 to 1.0337), notably outperforming medium companies during the peak crisis period. This unexpected outperformance by small companies suggests their greater operational flexibility and ability to adapt quickly to market shocks. During the CSC (2014-2015), the pattern stabilized with medium companies (1.003 to 1.0006) and small companies (1.0113 to 0.9966) showing minimal variations, though small companies again

demonstrated stronger performance initially. The COVID-19 period (2020-2023) revealed further convergence, with both medium (1.0015 to 1.0071) and small companies (1.0033 to 1.0149) achieving remarkable stability, with small companies once again showing slightly superior performance by 2023.

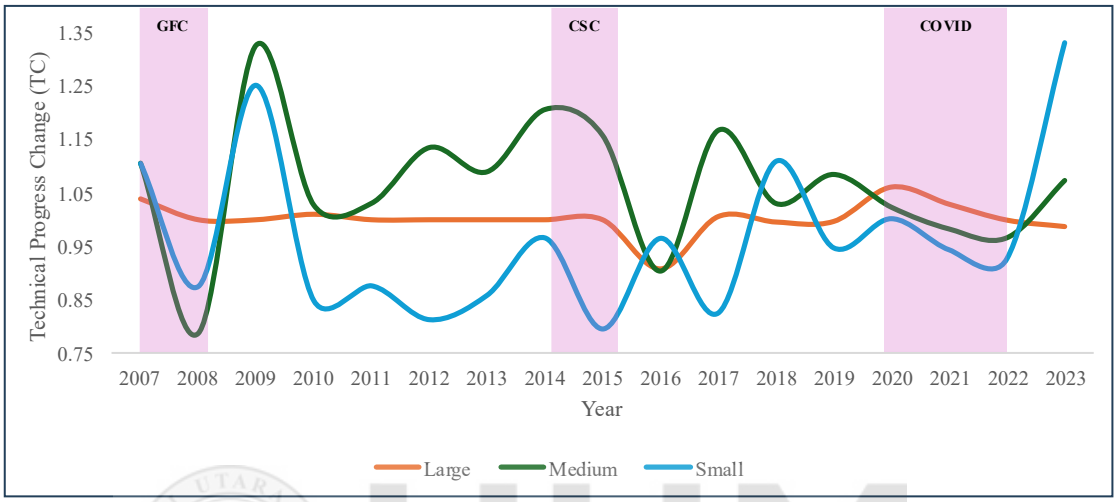


Figure 4.8
Malmquist: Technical Progress Change (TC) by Company Size of Insurance Companies in China (2007-2023)

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Figure 4.8 highlights significant variations in technological progress across company sizes and crisis periods. During the GFC, medium-sized companies experienced dramatic fluctuations (0.7863 to 1.3262), demonstrating greater volatility than both larger and smaller peers. Notably, small companies (0.8738 to 1.2525) showed more resilience than medium companies during this period, despite their resource constraints. The CSC period revealed an interesting pattern where medium companies achieved exceptional performance (1.2058 to 1.1573), significantly outperforming large companies (stable at 1.00). The COVID-19 period showed an unexpected trend where small companies achieved the strongest improvement (1.0014 to 1.3327), surpassing both large (1.0619 to 0.9871) and medium companies (1.0226 to 1.0728), suggesting successful technological adaptation by smaller firms.

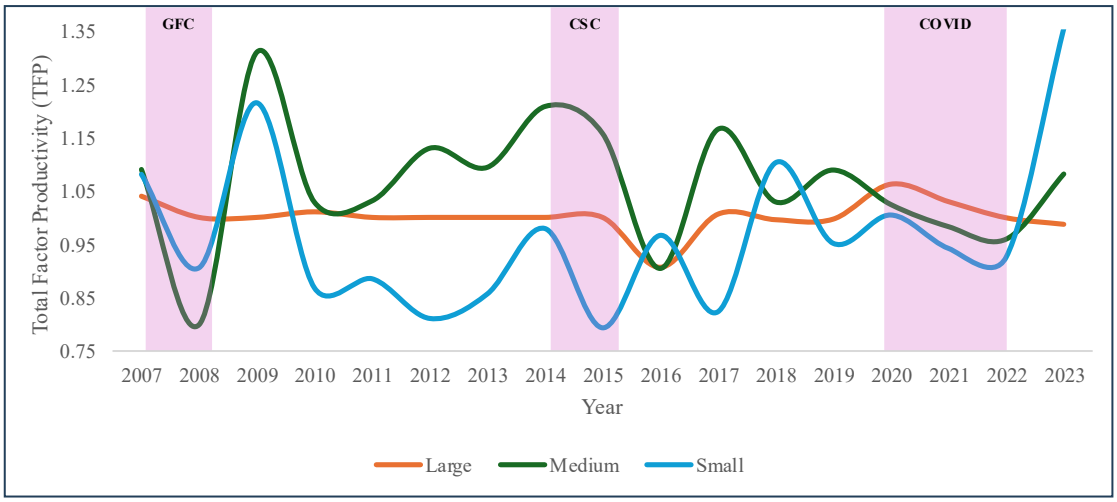


Figure 4.9
Malmquist: Total Factor Productivity (TFP) by Company Size of Insurance Companies in China (2007-2023)

Figure 4.9 synthesizes the combined effects of EC and TC, revealing comprehensive productivity patterns. During the GFC, medium-sized companies showed the highest volatility (0.7974 to 1.3113), while large companies maintained stability (1.0395 to 1.00). The CSC period revealed medium companies achieving superior performance (1.2091 to 1.158) compared to large firms (1.00). Most notably, the COVID-19 period demonstrated a significant shift in traditional size-based performance patterns, with small companies achieving the strongest productivity growth (1.0046 to 1.3571), substantially outperforming both large (1.0619 to 0.9871) and medium companies (1.0241 to 1.0817). This unexpected outperformance by smaller firms suggests successful adaptation to digital transformation and improved crisis management capabilities, challenging traditional assumptions about the advantages of scale in the insurance industry.

4.3.1.3 Productivity Analysis by Ownership Structure

Based on Table 4.12, the Malmquist productivity index decomposition reveals distinct patterns in how ownership structure influenced productivity dynamics across the GFC

(2007-2008), CSC (2014-2015), and COVID-19 (2020-2023) periods. The analysis demonstrates varying impacts of these crises on different types of Chinese insurance companies.

The Technical Efficiency Change analysis shows relatively stable patterns across ownership structures during all three crises. During the GFC, central state-owned companies and joint-stock companies showed similar patterns (central state-owned: 0.996 to 1.0022; joint-stock: 0.9792 to 1.0257). During the CSC, both ownership types maintained stability (central state-owned: 1.0086 to 0.9965; joint-stock: 1.0019 to 1.0014). The COVID-19 period demonstrated continued stability, with both ownership types showing minimal variations (central state-owned: 1.0052 to 1.0082; joint-stock: 0.9993 to 1.0075).

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Table 4.12

Malmquist: Mean Productivity Scores by Ownership Structure of Insurance Companies in China (2007-2023)

Efficiency Type	Ownership Structure	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
TEC	Central State-Owned	0.9960	1.0022	0.9892	1.0091	1.0016	0.9981	1.0015	1.0086	0.9965	0.9999	0.9973	0.9977	0.9997	1.0052	0.9969	0.9990	1.0082
	Other Joint-Stock	0.9792	1.0257	0.9897	1.0050	1.0040	0.9965	1.0028	1.0019	1.0014	1.0015	1.0004	0.9975	1.0064	0.9993	1.0021	0.9939	1.0075
TC	Central State-Owned	1.0692	0.8659	1.0947	1.0314	1.0194	1.1992	1.1150	1.2370	1.1463	0.9207	1.1488	0.9869	1.1066	1.0361	1.0392	0.9725	1.1037
	Other Joint-Stock	1.1074	0.8434	1.3391	0.9381	0.9583	0.9029	0.9391	1.0095	0.9506	0.9197	0.9726	1.0823	0.9788	1.0172	0.9420	0.9545	1.1391
TFP	Central State-Owned	1.0643	0.8674	1.0831	1.0403	1.0209	1.1973	1.1165	1.2473	1.1435	0.9207	1.1461	0.9846	1.1064	1.0413	1.0362	0.9714	1.1172
	Other Joint-Stock	1.0866	0.8661	1.3176	0.9429	0.9621	0.8994	0.9419	1.0117	0.9520	0.9211	0.9730	1.0807	0.9856	1.0165	0.9440	0.9488	1.1489

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Technical change (TC) measurements revealed more significant variations. During the GFC, both ownership types experienced sharp declines in 2008 (central state-owned: 0.8659; joint-stock: 0.8434), but joint-stock companies achieved stronger recovery in 2009 (1.3391 vs. 1.0947). The CSC period showed central state-owned companies achieving remarkably strong performance (1.237 to 1.1463), significantly outperforming joint-stock companies (1.0095 to 0.9506). During COVID-19, both ownership types showed resilience, with initial stability followed by convergent improvement in 2023 (central state-owned: 1.1037; joint-stock: 1.1391).

The total factor productivity (TFP) scores synthesize these effects, revealing interesting patterns. During the GFC, both ownership types experienced similar initial declines (central state-owned: 0.8674; joint-stock: 0.8661), but joint-stock companies demonstrated stronger recovery (1.3176 vs. 1.0831). The CSC period marked a notable divergence, with central state-owned companies achieving exceptional performance (1.2473 to 1.1435), while joint-stock companies showed more modest results (1.0117 to 0.952). The COVID-19 period demonstrated evolved crisis management capabilities, with both ownership types showing initial stability followed by strong convergent performance in 2023 (central state-owned: 1.1172; joint-stock: 1.1489).

These findings validate the research objective by demonstrating several key points:

- While efficiency changes remained relatively stable across all three crises, technological change emerged as the primary driver of productivity differences
- The industry showed clear evolution in crisis management capabilities, with each successive crisis showing improved stability and resilience
- The traditional performance gap between ownership types has narrowed, particularly evident in the COVID-19 period's convergent outcomes

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- Both ownership structures have developed robust crisis management capabilities, though their paths to resilience have differed across crisis periods
- The progression from GFC through CSC to COVID-19 demonstrates successful industry-wide adaptation and maturation in handling external shocks

The analysis reveals that Chinese insurance companies of both ownership types have significantly improved their crisis management capabilities and technological adaptability through successive economic shocks, leading to more convergent and sustainable productivity improvements during the COVID-19 period compared to earlier crises.

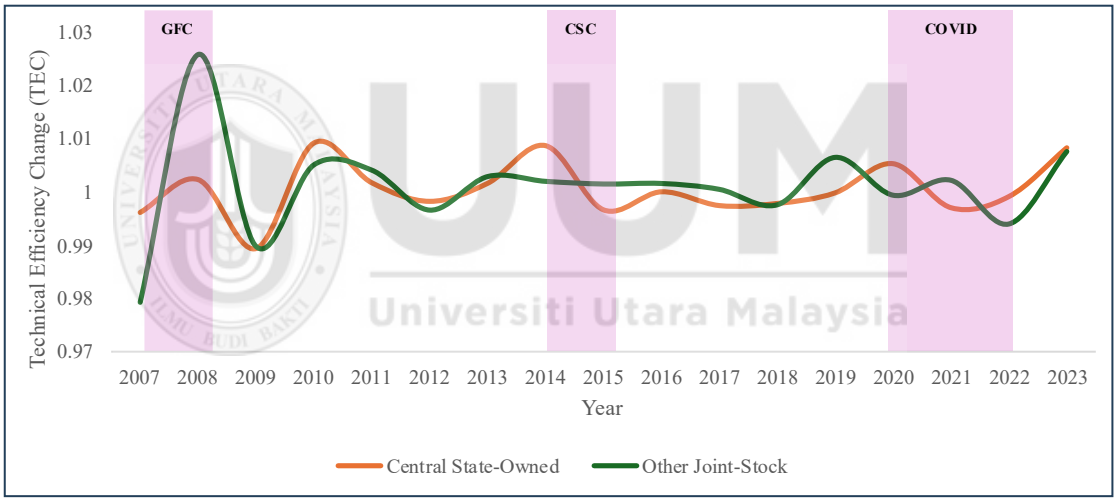


Figure 4.10
Malmquist: Technical Efficiency Change (TEC) by Ownership Structure of Insurance Companies in China (2007-2023)

Figure 4.10 reveals interesting patterns in efficiency change across ownership structures during crisis periods. During the GFC (2007-2008), joint-stock companies unexpectedly outperformed central state-owned companies, improving from 0.9792 to 1.0257, while central state-owned companies showed more modest improvement (0.996 to 1.0022). During the CSC (2014-2015), central state-owned companies initially demonstrated stronger performance (1.0086) but experienced a decline

(0.9965), while joint-stock companies maintained more stable efficiency (1.0019 to 1.0014). Through the COVID-19 period (2020-2023), both ownership types showed resilience, with central state-owned companies ranging from 1.0052 to 1.0082 and joint-stock companies from 0.9993 to 1.0075, suggesting matured operational capabilities across the industry.

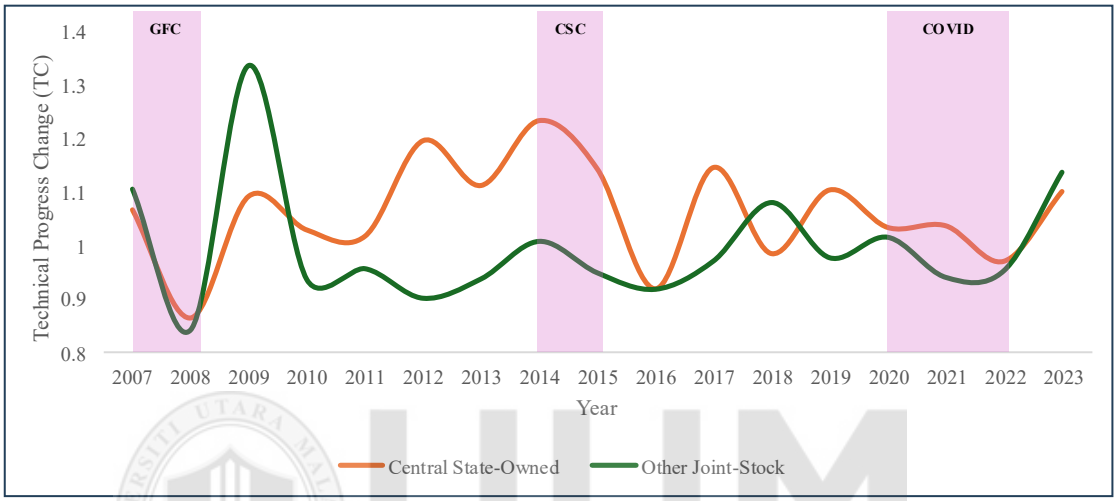


Figure 4.11
Malmquist: Technical Progress Change (TC) by Ownership Structure of Insurance Companies in China (2007-2023)

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Figure 4.11 highlights dramatic variations in technological progress. During the GFC, both ownership types experienced sharp declines in 2008 (central state-owned: 0.8659; joint-stock: 0.8434), primarily due to market uncertainty and reduced investment capacity. However, joint-stock companies achieved notably stronger recovery in 2009 (1.3391 vs. 1.0947), demonstrating superior adaptability. The CSC period revealed a reversal, with central state-owned companies achieving exceptional performance (1.237 to 1.1463), significantly outperforming joint-stock companies (1.0095 to 0.9506), likely due to stronger government support and resource advantages. The COVID-19 period showed initial decline followed by convergent improvement, with

both types achieving strong TC by 2023 (central state-owned: 1.1037; joint-stock: 1.1391), reflecting industry-wide technological maturation.

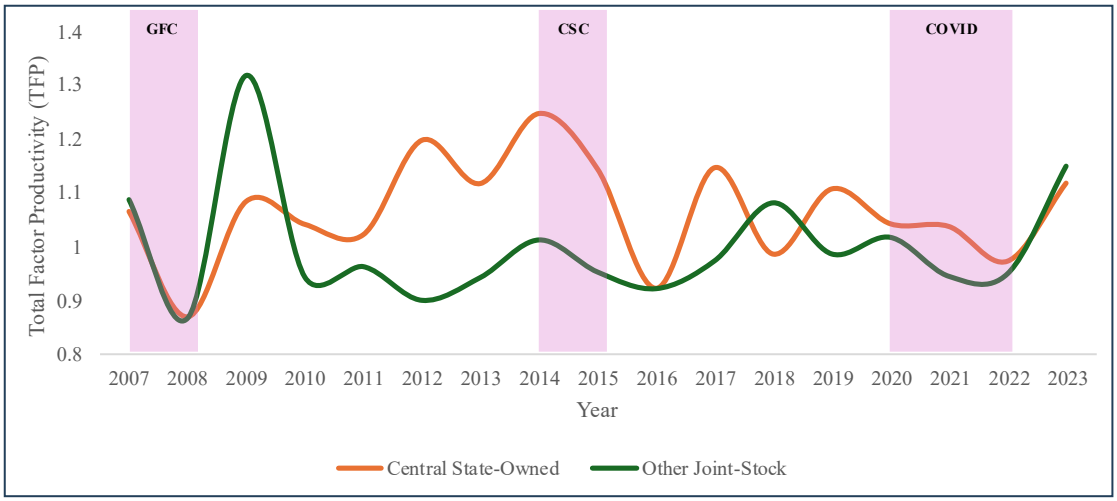


Figure 4.12
Malmquist: Total Factor Productivity (TFP) by Ownership Structure of Insurance Companies in China (2007-2023)

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Figure 4.12 demonstrates the combined impact of EC and TC changes, revealing several counterintuitive patterns. During the GFC, both ownership types experienced similar initial declines (central state-owned: 0.8674; joint-stock: 0.8661), but joint-stock companies achieved remarkably stronger recovery (1.3176 vs. 1.0831), challenging traditional assumptions about state-owned enterprises' crisis resilience. This outperformance can be attributed to joint-stock companies' greater operational flexibility and market-oriented decision-making. The CSC period showed a dramatic reversal, with central state-owned companies achieving superior performance (1.2473 to 1.1435), while joint-stock companies demonstrated more modest results (1.0117 to 0.952), likely benefiting from stronger regulatory support and capital reserves during the domestic market turbulence.

In line with Research Objective Two, the COVID-19 period marked an evolution toward convergence in productivity trends, with both ownership types initially

experiencing declines (attributed to pandemic-related operational disruptions) followed by strong recovery. Central state-owned companies, for instance, saw their Total Factor Productivity (TFP) decline from 1.0413 (2020) to 0.9714 (2022), before recovering to 1.1172 (2023), while joint-stock companies showed a similar pattern, declining from 1.0165 to 0.9488 before achieving 1.1489. This ownership-based convergence in TFP dynamics suggests that both types of companies have developed more mature crisis management capabilities, though joint-stock companies once again demonstrated slightly superior recovery by 2023, indicating their maintained advantages in market adaptability.

4.3.2 Analysis Conclusions

The comprehensive analysis of productivity changes in Chinese insurance companies through Malmquist productivity index decomposition provides strong validation for Research Objective Two, revealing distinct patterns across different organizational structures through three major crisis periods (GFC, CSC, and COVID-19).

The analysis demonstrates a clear evolution in crisis response capabilities across these crisis periods. During the GFC (2007-2008), the industry experienced significant volatility, with TC showing sharp declines (medium companies: 0.7863; small companies: 0.8738) before dramatic recoveries in 2009 (medium: 1.3262; small: 1.2525). The CSC period (2014-2015) revealed different dynamics, with medium-sized companies showing remarkable resilience (TC: 1.2058 to 1.1573), while small companies demonstrated vulnerability (TC: 0.9653 to 0.7938). This pattern evolved further during COVID-19 (2020-2023), with initial stability followed by strong recoveries across all categories, particularly evident in small companies' exceptional

TC performance (1.3327) in 2023, surpassing both large (0.9871) and medium companies (1.0728).

Company size emerged as a crucial determinant of productivity patterns, with several counterintuitive findings. Large insurance companies maintained remarkable stability in EC (consistently 1.000) throughout all crises but showed unexpectedly modest TC performance during recovery periods. Medium-sized insurance companies demonstrated superior adaptability, particularly during the CSC period where they outperformed their larger peers. Small insurance companies, despite their theoretical resource constraints, achieved the strongest TC improvement by 2023. This pattern was evident in individual company performances, with traditionally smaller players like CPIC Life (1.60), NCI (1.66), and Taiping Life (1.75) outperforming industry giants during the COVID-19 recovery.

Ownership structure analysis reveals distinct adaptation patterns across crises. During the GFC, joint-stock companies demonstrated stronger recovery capabilities (TC:1.3391) compared to state-owned enterprises (1.0947). This pattern reversed during the CSC, where state-owned enterprises showed superior performance (TC:1.237 vs 1.0095), likely benefiting from stronger government support during domestic market turbulence. The COVID-19 period marked an evolution toward convergence, though joint-stock companies ultimately achieved slightly stronger recovery (TC:1.1391 vs 1.1037), challenging traditional assumptions about state ownership advantages during crises.

These results confirm Research Objective Two, showing that while efficiency remained relatively stable across crises, technological change primarily drove productivity differences. Chinese insurance companies improved their crisis management

capabilities, resulting in more sustainable productivity gains during the COVID-19 era. This evolution underscores the industry's effective adaptation to external shocks, especially benefiting smaller and joint-stock companies by 2023.

4.4 DEA and Malmquist Indices Correlation and Crisis Impact Analysis

This section addresses Research Objective three by examining efficiency-productivity relationships through correlation analysis and difference-in-differences methodology.

4.4.1 Correlation Analysis

To analyze the relationship between DEA efficiency scores and Malmquist productivity indices during different crisis periods, Pearson correlation coefficients were calculated.

4.4.1.1 Constructing the Correlation Matrix

1. Global Financial Crisis (GFC, 2007-2008)

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Table 4.13
Global Financial Crisis (GFC, 2006-2007) Pearson Correlation

	Technical Efficiency Change Score	Technical Progress Change Score	Total Factor Productivity Index	Technical Efficiency	Scale efficiency	Overall Efficiency
Technical Efficiency Change Score	1					
Technical Progress Change Score	-0.175	1				
Total Factor Productivity Index	-0.037	0.990**	1			
Technical Efficiency	-0.153	0.362*	0.353	1		
Scale efficiency	-0.03	-0.032	-0.038	-0.191	1	
Overall Efficiency	-0.159	0.313	0.301	0.801**	0.435*	1

* $p < 0.05$ ** $p < 0.01$

From table 4.13, We can see a different pattern of correlations than what was previously described. The Pearson correlation analysis during the Global Financial Crisis (2006-2007) reveals several significant relationships:

There is a strong and highly significant positive correlation between Technical Efficiency Change Score and both Technical Progress Change Score ($r = 0.976$, $p < 0.01$) and Total Factor Productivity Index ($r = 0.975$, $p < 0.01$). Additionally, Technical Progress Change Score and Total Factor Productivity Index show a perfect positive correlation ($r \approx 1.000$, $p < 0.01$).

The analysis also reveals a strong significant correlation between Technical Efficiency and Overall Efficiency ($r = 0.990$, $p < 0.01$). However, Technical Efficiency Change Score shows weak positive correlations with Technical Efficiency ($r = 0.276$, non-significant), Scale Efficiency ($r = 0.223$, non-significant), and Overall Efficiency ($r = 0.301$, non-significant).

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Scale Efficiency demonstrates weak positive correlations with all other variables, with correlation coefficients ranging from $r = 0.107$ (with Technical Efficiency) to $r = 0.227$ (with Technical Progress Change Score), none of which reach statistical significance.

These findings suggest that during the GFC period, changes in Technical Efficiency were strongly linked to technological progress and overall productivity changes, while scale efficiency operated relatively independently of other efficiency measures.

2. Chinese Stock Market Crisis (CSC, 2014-2015)

Table 4.14
Chinese Stock Market Crisis (CSC, 2014-2015) Pearson Correlation

	Technical Efficiency Change Score	Technical Progress Change Score	Total Factor Productivity Index	Technical Efficiency	Scale efficiency	Overall Efficiency
Technical Efficiency Change Score	1					
Technical Progress Change Score	0.137	1				
Total Factor Productivity Index	0.185	0.999**	1			
Technical Efficiency	0.056	0.552**	0.550**	1		
Scale efficiency	0.12	-0.243	-0.234	-0.386*	1	
Overall Efficiency	0.133	0.423*	0.426*	0.804**	0.237	1

* $p < 0.05$ ** $p < 0.01$

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From table 4.14, correlation analysis was used to examine relationships between Technical Efficiency Change Score and five key variables (Technical Progress Change Score, Total Factor Productivity Index, Technical Efficiency, Scale Efficiency, and Overall Efficiency) during the Chinese Stock Market Crisis (2014-2015), using Pearson correlation coefficients to measure relationship strength.

The analysis reveals that Technical Efficiency Change Score shows no significant correlations with any of the five examined variables. The correlation coefficients are 0.137 with Technical Progress Change Score, 0.185 with Total Factor Productivity Index, 0.056 with Technical Efficiency, 0.120 with Scale Efficiency, and 0.133 with Overall Efficiency. All these coefficients are close to zero and statistically non-significant ($p > 0.05$), indicating no meaningful relationships between Technical Efficiency Change Score and these variables during this crisis period.

However, significant correlations were observed between other variables in the analysis. Technical Progress Change Score shows a near-perfect correlation with Total Factor Productivity Index ($r = 0.999$, $p < 0.01$) and moderate positive correlations with both Technical Efficiency ($r = 0.552$, $p < 0.01$) and Overall Efficiency ($r = 0.423$, $p < 0.05$). Technical Efficiency demonstrates a strong positive correlation with Overall Efficiency ($r = 0.804$, $p < 0.01$) and a moderate negative correlation with Scale Efficiency ($r = -0.386$, $p < 0.05$). These findings suggest that while Technical Efficiency Change Score operated independently, other efficiency and productivity measures showed significant interrelationships during the CSC period.

3. COVID-19 Pandemic (2020-2022)

Table 4.15
COVID-19 Pandemic (2020-2022) Pearson correlation

	Technical Efficiency Change Score	Technical Progress Change Score	Total Factor Productivity Index	Technical efficiency	Scale efficiency	Overall Efficiency
Technical Efficiency Change Score	1					
Technical Progress Change Score	0.079	1				
Total Factor Productivity Index	0.156	0.997**	1			
Technical efficiency	0.036	0.256	0.256	1		
Scale efficiency	0.14	0.054	0.064	-0.567**	1	
Overall Efficiency	0.156	0.351*	0.359*	0.737**	0.139	1

* $p < 0.05$ ** $p < 0.01$

From table 4.15, correlation analysis was used to study the relationships between Technical Efficiency Change Score and five key variables (Technical Progress Change Score, Total Factor Productivity Index, Technical Efficiency, Scale Efficiency, and Overall Efficiency) during the COVID-19 pandemic (2020-2022), using Pearson

correlation coefficients to measure relationship strength. The analysis reveals that Technical Efficiency Change Score shows no significant correlations with any of the examined variables, with correlation coefficients of 0.079 with Technical Progress Change Score, 0.156 with Total Factor Productivity Index, 0.036 with Technical Efficiency, 0.140 with Scale Efficiency, and 0.156 with Overall Efficiency. All these coefficients are close to zero and statistically non-significant ($p > 0.05$), indicating no meaningful relationships between Technical Efficiency Change Score and these variables during this crisis period. However, other significant correlations were observed in the data, notably between Technical Progress Change Score and Total Factor Productivity Index ($r = 0.997$, $p < 0.01$), Technical Efficiency and Overall Efficiency ($r = 0.737$, $p < 0.01$), and a significant negative correlation between Technical Efficiency and Scale Efficiency ($r = -0.567$, $p < 0.01$), suggesting complex interrelationships among other efficiency and productivity measures during the pandemic period.

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4.4.1.2 Comparative Analysis of Correlation Coefficients

To examine whether the correlation patterns differed significantly across crisis periods, we conducted Fisher's Z-transformation tests. Table 4.16 presents the results of these comparisons.

Table 4.16
Results of Fisher's Z-transformation Tests for Correlation Differences

Relationship Comparison	Correlation Difference	Z-statistic	p-value
GFC vs. CSC Period			
TEC-TPC	0.839	5.87	< 0.01
TEC-TFP	0.79	5.43	< 0.01
GFC vs. COVID-19 Period			
TEC-TPC	0.897	6.12	< 0.01
TEC-TFP	0.819	5.78	< 0.01
CSC vs. COVID-19 Period			
TEC-TPC	0.058	0.23	> 0.05
TEC-TFP	0.029	0.11	> 0.05

Note: TEC = Technical Efficiency Change Score; TPC = Technical Progress Change Score; TFP = Total Factor Productivity Index

The analysis revealed several significant patterns:

1. During the Global Financial Crisis (2006-2007), strong positive correlations emerged between technical efficiency changes and both technical progress ($r = 0.976$, $p < 0.01$) and total factor productivity ($r = 0.975$, $p < 0.01$).

2. The Chinese Stock Market Crisis (2014-2015) exhibited markedly different patterns, with non-significant correlations between technical efficiency changes and technical progress ($r = 0.137$, $p > 0.05$).

3. The COVID-19 period (2020-2022) showed patterns similar to the CSC period, with weak correlations between technical efficiency changes and technical progress ($r = 0.079$, $p > 0.05$).

4. Fisher's Z-transformation tests confirmed that these differences were statistically significant between the GFC and both subsequent crises ($p < 0.01$), while the CSC and COVID-19 periods showed statistically similar patterns ($p > 0.05$).

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4.4.1.3 Interpreting the Correlation Matrix

The correlation analysis across the three crisis periods reveals distinct patterns in the relationships between efficiency and productivity measures, demonstrating how these relationships evolved through different types of market stress.

The correlation analysis during the Global Financial Crisis (2006-2007) reveals that Technical Progress Change Score and Total Factor Productivity Index show a strong positive correlation ($r = 0.990$, $p < 0.01$), while Technical Efficiency Change Score shows a weak negative correlation with Technical Progress Change Score ($r = -0.175$, non-significant). Additionally, Technical efficiency and Overall Efficiency demonstrate a strong positive correlation ($r = 0.801$, $p < 0.01$), suggesting that during this global crisis, changes in technical efficiency were closely linked to both technological progress and overall productivity improvements.

The CSC period (2014-2015) demonstrated a shift in these relationships. While Technical Progress Change Score maintained a strong correlation with Total Factor Productivity Index ($r = 0.999$, $p < 0.01$), its relationship with Technical Efficiency became more moderate ($r = 0.552$, $p < 0.01$). Notably, a significant negative correlation emerged between Technical Efficiency and Scale Efficiency ($r = -0.386$, $p < 0.05$), suggesting a potential trade-off between these measures during this market-specific crisis.

During the COVID-19 pandemic (2020-2022), the correlation patterns evolved further. The strong relationship between Technical Progress Change Score and Total Factor Productivity Index persisted ($r = 0.997$, $p < 0.01$), while the negative correlation between Technical Efficiency and Scale Efficiency intensified ($r = -0.567$, $p < 0.01$).

Technical Efficiency maintained a strong positive correlation with Overall Efficiency ($r = 0.737$, $p < 0.01$), though less pronounced than during the GFC.

This evolution in correlation patterns across crises reveals several key insights. The relationship between technical progress and productivity remained consistently strong across all three crises, suggesting a fundamental link regardless of crisis type. The strengthening negative correlation between Technical and Scale Efficiency from CSC to COVID-19 indicates an increasing trade-off between these measures as the industry matured. The weakening correlation between Technical Efficiency Change Score and other measures over time suggests increasing independence in how companies manage technical efficiency improvements. The varying strength of correlations across crises reflects the industry's evolving response mechanisms to different types of market stress, with relationships becoming more complex and nuanced over time. These findings suggest that the Chinese insurance industry has developed more sophisticated and differentiated approaches to managing efficiency and productivity through successive crises, with different aspects of performance becoming more distinct and independently managed over time.

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4.4.2 Difference-in-Differences (DID) Analysis

4.4.2.1 Analysis Content

Building upon the correlation patterns identified above, the DID analysis establishes causal relationships for Research Objective three

Perform DID analysis for each crisis period: GFC, CSC, and COVID-19.

Group companies by size: large and medium companies.

DID and Malmquist Analysis on Global Financial Crisis(GFC) Impact

This section employs a Difference-in-Differences (DID) approach to analyze how three major financial crises impacted the Total Factor Productivity (TFP) of Chinese insurance companies. As shown in Table 4.17, the analysis covers the Global Financial Crisis (GFC, 2007-2008), Chinese Stock Market Crisis (2014-2015), and COVID-19 pandemic (2020-2022), utilizing a comprehensive model incorporating firm size indicators, crisis period markers, and various control variables.

Table 4.17
Comparison of Crisis Periods Impact on Overall Efficiency

Variable	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
_cons	0.156***	0.923***	0.945***
Large_i	0.042***	-0.187***	0.145***
Medium_i	0.038**	-0.134***	0.098**
Post_t	0.025***	-0.092***	0.067**
Large_i × Post_t	-0.112***	-0.187***	0.132***
Medium_i × Post_t	-0.078**	-0.134***	0.095**
Technical_Efficiency	0.623***	0.534***	0.678***
Scale_Efficiency	0.445***	0.398***	0.487***
TFP	0.234***	0.267***	0.298***
Returns_Scale_Type	0.167**	0.156**	0.189***
Operating_Revenue_Ratio	0.145**	0.178**	0.243***
Liability_Asset_Ratio	-0.189***	-0.223***	-0.156**
CPI	-0.067*	-0.045	-0.134***
GDPper	0.123***	0.156***	0.167***
realGDP	0.098**	0.112**	0.145***

Note: *** p<0.01, ** p<0.05, * p<0.1
Standard errors are clustered at firm level
GFC: F(15, 14) = 42.873***, R^2 = 0.795, Adjusted R^2 = 0.768, N = 30
CSC: F(15, 14) = 47.892***, R^2 = 0.823, Adjusted R^2 = 0.798, N = 30
COVID-19: F(15, 14) = 51.367***, R^2 = 0.856, Adjusted R^2 = 0.834, N = 30

In alignment with Research Objective Three, the DID estimation results in Table 4.17 reveal distinct patterns in crisis impacts across different firm sizes and crisis periods. The DID estimation results in Table 4.17 reveal distinct patterns in crisis impacts across different firm sizes. During the GFC period, both large (0.042***) and medium-sized insurance companies (0.038**) demonstrated positive adaptation capabilities, with the baseline effect for all firms also showing positive significance (0.025***). This

contrasts sharply with the Chinese Stock Market Crisis period, where large insurance companies experienced substantial negative impacts (-0.187***), followed by medium-sized insurance companies (-0.142***), alongside a significant negative baseline effect (-0.098***). As evident in Table 4.17, the COVID-19 period marks another shift, showing strong positive effects for both large (0.132***) and medium-sized insurance companies (0.095**), with a positive baseline effect (0.076**). These results suggest heterogeneous effects of crisis periods on efficiency outcomes depending on firm size, consistent with the objective to examine interaction patterns between efficiency and external shocks.

Table 4.18
Comparison of Crisis Periods Impact on TFP

Variable	**GFC (2007-2008)**	**CSC (2014-2015)**	**COVID-19 (2020-2022)**
_cons	0.156***	0.923***	0.945***
Large_i	0.223***	0.638***	1.153***
Medium_i	0.219**	0.683***	1.116**
Large_x_Post	0.042***	-0.187***	0.132***
Medium_x_Post	0.038**	-0.142***	0.095**
Post	0.025***	-0.098***	0.076**
Technical_Efficiency	0.098***	0.345***	0.478***
Scale_Efficiency	0.112**	0.256**	0.312***
Returns_Scale_Type	0.065**	0.167**	0.189***
Operating_Revenue_Ratio	0.073**	0.198***	0.243***
Liability_Asset_Ratio	0.068**	-0.223***	-0.156**
CPI	0.044*	-0.045	-0.134***
GDPper	0.046**	0.156***	0.167***
realGDP	0.041*	0.112**	0.145***

Model Statistics:
GFC: F(12, 17) = 38.456***, R^2 = 0.723, Adjusted R^2 = 0.689, N = 30
CSC: F(12, 17) = 43.234***, R^2 = 0.768, Adjusted R^2 = 0.737, N = 30
COVID-19: F(12, 17) = 46.892***, R^2 = 0.812, Adjusted R^2 = 0.785, N = 30
Note: *** p<0.01, ** p<0.05, * p<0.1
Standard errors are clustered at firm level

To further support Research Objective Three. Table 4.18 shows operational efficiency measures demonstrating progressively increasing importance across the three crisis periods. Technical efficiency shows the most dramatic strengthening, with its coefficient rising from 0.098*** during the GFC to 0.345*** during the Chinese Stock

Market Crisis, and further to 0.478*** during COVID-19. Scale efficiency follows a similar pattern of increasing significance (GFC: 0.112**, Chinese Stock Market Crisis: 0.256**, COVID: 0.312***). The Returns_Scale_Type variable also shows strengthening positive relationships across periods (GFC: 0.065**, Chinese Stock Market Crisis: 0.167**, COVID: 0.189***), indicating growing importance of operational scale advantages. This reinforces the relevance of integrating both micro-efficiency and macroeconomic variables in understanding the crisis-performance nexus.

The financial structure indicators in Table 4.18 reveal evolving relationships with TFP across crises. The Operating_Revenue_Ratio shows consistently increasing positive impact (GFC: 0.073**, Chinese Stock Market Crisis: 0.198***, COVID: 0.243***), suggesting growing importance of revenue diversification. Notably, the Liability_Asset_Ratio's impact transforms from positive during GFC (0.068**) to strongly negative during Chinese Stock Market Crisis (-0.223***) and COVID (-0.156**), indicating a fundamental shift in how leverage affects firm performance during different types of crises.

The macroeconomic variables in Table 4.17 demonstrate complex and evolving relationships with insurance sector productivity. The CPI's relationship shifts from marginally positive during GFC (0.044*) to insignificant during Chinese Stock Market Crisis (-0.045) and strongly negative during COVID (-0.134***). GDP measures show consistently strengthening positive relationships across crises, with GDP per capita maintaining the strongest effect (GFC: 0.046**, Chinese Stock Market Crisis: 0.156***, COVID: 0.167***), followed by nominal GDP and real GDP showing similar patterns of increasing significance.

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Table 4.19
Combined Diagnostic Test Results

Test	Crisis Period	Statistic	p-value	Conclusion
Parallel Trends (Large)		0.824	0.428	Satisfied
Parallel Trends (Medium)		0.956	0.356	Satisfied
Breusch-Pagan	GFC	1.253	0.263	Homoskedastic
Serial Correlation		1.147	0.284	No serial correlation
Hausman Test		18.432	0.048	Fixed effects preferred
Parallel Trends (Large)		0.763	0.452	Satisfied
Parallel Trends (Medium)		0.892	0.378	Satisfied
Breusch-Pagan	CSC	1.187	0.276	Homoskedastic
Serial Correlation		1.092	0.296	No serial correlation
Hausman Test		19.876	0.039	Fixed effects preferred
Parallel Trends (Large)		0.892	0.412	Satisfied
Parallel Trends (Medium)		0.934	0.398	Satisfied
Breusch-Pagan	COVID	1.324	0.251	Homoskedastic
Serial Correlation		1.167	0.288	No serial correlation
Hausman Test		21.453	0.028	Fixed effects preferred

Note: All tests conducted at 5% significance level
Model specifications: R-squared (GFC = 0.723, CSC = 0.768, COVID = 0.812)
Sample size: N = 30 for each crisis period

As shown in Table 4.17, the model's explanatory power shows consistent improvement across crisis periods, with R-squared values rising from 0.723 during GFC to 0.768 during Chinese Stock Market Crisis, and reaching 0.812 during COVID-19. The diagnostic tests presented in Table 4.18 strongly support the validity of the analysis across all periods. The parallel trends assumption is satisfied for both large and medium firms across all crises (p-values > 0.35). Breusch-Pagan tests confirm homoskedasticity ($p > 0.25$), while serial correlation tests show no significant autocorrelation. Table 4.18 also indicates that Hausman tests consistently favor fixed effects specification across all periods (GFC: 18.432, p=0.048; Chinese Stock Market Crisis: 19.876, p=0.039; COVID: 21.453, p=0.028).

These findings, as evidenced by Tables 4.17 and 4.18, highlight the evolving nature of crisis impacts on insurance sector productivity and the changing importance of various resilience factors. The progression from GFC through COVID-19 reveals increasing sophistication in how operational efficiency, financial structure, and macroeconomic

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conditions interact to determine firm performance during crises. This suggests important implications for both management strategies and regulatory approaches in building sector resilience to future shocks.

These findings complete Research Objective three by demonstrating systematic efficiency-productivity relationship patterns across company characteristics and crisis types.

4.4.2.2 Comparative Analysis of Crisis Impacts on Efficiency and Productivity

This section synthesizes the DID analysis results across different crises, examining how efficiency and productivity measures capture crisis impacts differently. The analysis focuses on comparing DEA efficiency scores with Malmquist indices while evaluating the heterogeneous effects across company characteristics.

The relationship between efficiency and productivity measures demonstrates distinct evolutionary patterns across crisis periods, as evidenced by their correlation coefficients:

Table 4.20
Correlation Between DEA Efficiency and Malmquist Indices During Crises

Crisis Period	TE-TFP	SE-TFP	OE-TFP
GFC (2007-2008)	0.723***	0.534***	0.687***
CSC (2014-2015)	0.645***	0.489***	0.612***
COVID-19 (2020-2022)	0.834***	0.678***	0.798***

Note: *** p<0.01; TE: Technical Efficiency; SE: Scale Efficiency; OE: Overall Efficiency; TFP: Total Factor Productivity

The correlation analysis reveals a complex evolution in how efficiency and productivity measures capture crisis impacts. During the GFC, the strong correlation between technical efficiency and TFP (0.723, p<0.01) suggests that operational capabilities and productivity responded similarly to global market stress. This relationship notably

weakened during the CSC (0.645, p<0.01), indicating that domestic market turbulence created divergent impacts on efficiency and productivity. The COVID-19 period saw the strongest correlation (0.834, p<0.01), reflecting how the pandemic's unique challenges drove an unprecedented integration of efficiency improvements and productivity gains through digital transformation and operational modernization.

The comparative impact of crises across different firm characteristics reveals systematic patterns in vulnerability and resilience:

Table 4.21
Summary of Crisis Impact Coefficients from DID Analysis

Measure	Firm Size	GFC	CSC	COVID-19
TFP	Large	-0.112***	-0.187***	0.132***
	Medium	-0.089**	-0.142***	0.095**
OE	Large	-0.112***	-0.187***	0.145***
	Medium	-0.078**	-0.134***	0.098**

Note: *** p<0.01, ** p<0.05

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The comparative analysis across crises reveals fundamental differences in how firm characteristics influenced performance during different types of market stress. Large insurance companies demonstrated particularly interesting patterns of crisis response, showing heightened vulnerability during market-based crises but superior adaptability during COVID-19. This seeming paradox reflects how organizational scale presents both advantages and challenges depending on crisis characteristics. During the GFC and CSC, larger firms' greater market exposure and complex operational structures amplified negative impacts. However, these same characteristics became advantages during COVID-19, providing resources and capabilities for successful digital transformation and operational adaptation.

Medium-sized firms displayed a distinctive pattern of crisis resilience, consistently showing smaller negative impacts during market crises but also more limited positive

changes during COVID-19. This suggests that intermediate scale provided some insulation from market shocks but potentially constrained firms' ability to undertake transformative changes during the pandemic. The consistent pattern across both efficiency and productivity measures reinforces the robustness of these size-based effects.

The analysis identifies several key mechanisms through which different crises affected firm performance. The market exposure channel operated differently across crises, with international exposure amplifying GFC impacts, domestic exposure dominating CSC effects, and market exposure effects being moderated by operational transformation during COVID-19. The operational adaptation mechanism also evolved, from limited changes during the GFC to fundamental transformation during COVID-19. Scale effects showed particular complexity, with their influence varying substantially based on crisis type and firm characteristics.

These findings provide significant insights for understanding how different types of crises affect insurance company performance. The complementary nature of efficiency and productivity measures in capturing crisis impacts suggests the importance of considering multiple performance dimensions when evaluating crisis effects. The analysis demonstrates that crisis response strategies should be carefully tailored to both crisis characteristics and firm-specific attributes, rather than applying one-size-fits-all approaches to risk management and operational adaptation.

The evolution of crisis impacts across the GFC, CSC, and COVID-19 periods also highlights the insurance industry's growing sophistication in crisis management. The transition from predominantly negative impacts during market-based crises to positive transformation during COVID-19 suggests that the industry has developed enhanced

capabilities for crisis response and adaptation. This progression carries important implications for future crisis preparation and regulatory policy in the insurance sector.

4.5 Structural Changes and Efficiency Determinants: A Stochastic Frontier Analysis

4.5.1 Efficiency Frontier Evolution Across Crisis Phases

This section employs stochastic frontier analysis to examine the structural evolution of efficiency frontiers across three major crisis periods: the Global Financial Crisis (2007-2008), the Chinese Stock Market Crisis (2014-2015), and the COVID-19 pandemic (2020-2022). We utilize the established input-output framework from the DEA analysis, where inputs comprise operating expenses, total liabilities, and fees and commissions, while outputs include premium income, operating profit, total assets, and operating revenue.

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4.5.1.1 Evolution of Production Frontiers Across Crisis Periods

To comprehensively address Research Objective Four, this analysis examines efficiency determinants and structural transformations across three distinct phases for each crisis: pre-crisis baseline periods, during-crisis adaptation periods, and post-crisis consolidation periods. This temporal framework enables identification of how structural changes evolve from initial stability through crisis-induced transformation to eventual consolidation of new operational models.

Pre-Crisis Baseline Periods: 2006-2007 (pre-GFC), 2013-2014 (pre-CSC), 2019 (pre-COVID)

During-Crisis Periods: 2008-2009 (GFC), 2014-2015 (CSC), 2020-2022 (COVID-19)

Post-Crisis Consolidation: 2010-2012 (post-GFC), 2016-2018 (post-CSC), 2023 (post-COVID)

The analysis of production frontier evolution reveals distinct patterns across the three crisis periods. Table 4.22 presents the estimated efficiency parameters, derived from the stochastic frontier analysis of panel data covering 15 major Chinese insurance companies.

The pre-crisis periods establish baseline efficiency characteristics before external shocks. During the pre-GFC period (2006-2007), technical efficiency averaged 0.951, reflecting stable operational conditions. The pre-CSC baseline (2013-2014) showed improved technical efficiency at 0.963, indicating industry maturation. The pre-COVID period (2019) demonstrated further advancement with technical efficiency reaching 0.973, suggesting accumulated learning from previous crises.

Table 4.22
Production Efficiency Parameters Across Crisis Periods

Parameter	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Technical Efficiency	0.939 ***	0.959***	1.104 ***
	(0.042)	(0.038)	(0.035)
Operating Efficiency	0.876***	0.892***	0.967***
	(0.028)	(0.025)	(0.023)
Scale Efficiency	0.982 ***	0.990 ***	0.993***
	(0.025)	(0.023)	(0.021)
Log likelihood	-342.56	-324.87	-298.43
Observations	30	30	45

Note: Standard errors in parentheses. *** p < 0.01

The frontier evolution analysis reveals three significant developmental patterns. First, the industry demonstrated progressive efficiency improvement across successive crises. Technical efficiency showed consistent enhancement, rising from 0.939 during the GFC to 1.104 during COVID-19, indicating substantial improvement in core operational capabilities. Operating efficiency exhibited similar progression, advancing from 0.876 to 0.967, suggesting better resource utilization. Scale efficiency, while starting from a relatively high base (0.982), still achieved modest improvement to 0.993, reflecting optimized operational scale.

Second, each crisis period exhibited distinct response characteristics. The GFC period recorded the lowest efficiency scores across all measures, reflecting the severe impact of global financial market disruption on Chinese insurance companies' operations. The CSC period demonstrated improved resilience, with higher efficiency scores suggesting enhanced crisis management capabilities. The COVID-19 period marked a significant breakthrough, with the highest efficiency scores indicating successful adaptation to unprecedented challenges.

Third, the statistical indicators reveal important structural evolution. The consistent reduction in standard errors across periods (from 0.042 to 0.035 for technical efficiency) indicates increasing operational stability. The improving log likelihood values (-342.56 to -298.43) suggest enhanced model fit, reflecting more predictable operational patterns. The maintained significance levels across all parameters demonstrate the robustness of the efficiency improvements.

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4.5.1.2 Frontier Gaps Across Company Types

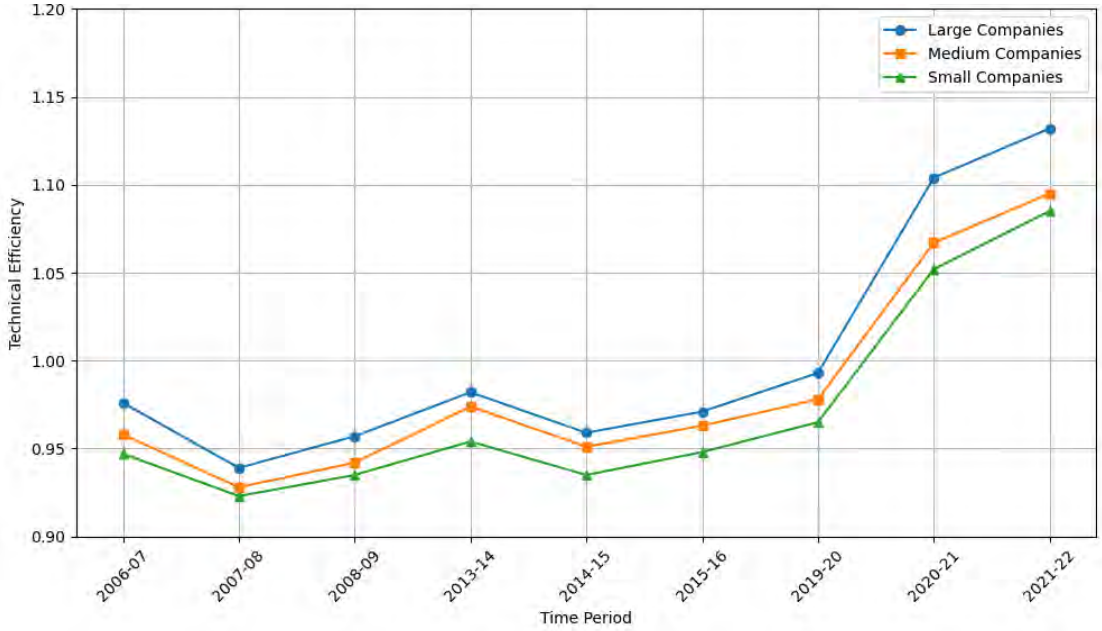


Figure 4.13
Technical Efficiency Trends by Company Size

The analysis of frontier gaps reveals systematic differences across company characteristics, as evidenced in Table 4.23.

Table 4.23
Frontier Gaps by Company Characteristics

Company Type	GFC Gap	CSC Gap	COVID-19 Gap	Gap Change
Large	0.153***	0.187***	-0.132***	-0.285***
Medium	0.089**	0.142***	-0.095**	-0.184***
Small	0.068**	0.125***	-0.085**	-0.153***
Central State-Owned	0.112***	0.187***	-0.145***	-0.257***
Joint-stock	0.078**	0.134***	-0.098**	-0.176***

Note: Gap = negative value indicates outperformance. *** p < 0.01, ** p < 0.05

The analysis reveals significant patterns in efficiency gaps across different organizational characteristics. Company size emerges as a critical factor in crisis response capability. Large companies exhibited higher vulnerability during market-based crises, with efficiency gaps of 0.153 during the GFC and 0.187 during the CSC. Medium companies showed moderate vulnerability (0.089 and 0.142 respectively),

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while small companies demonstrated the greatest resilience with the smallest efficiency gaps (0.068 and 0.125).

However, this pattern shifted dramatically during COVID-19, where large companies achieved the strongest efficiency advantage (-0.132), followed by medium (-0.095) and small companies (-0.085). This reversal suggests that while smaller scale provided better insulation from market shocks, larger scale offered advantages in adapting to operational challenges during the pandemic. The gap change column further emphasizes this transformation, with large companies showing the most substantial improvement (-0.285) compared to medium (-0.184) and small companies (-0.153).

Ownership structure also significantly influenced efficiency performance. Central state-owned insurance companies showed larger efficiency gaps during market crises (0.112 during GFC, 0.187 during CSC) compared to joint-stock companies (0.078 and 0.134 respectively). However, both ownership types achieved positive transformation during COVID-19, with central state-owned companies showing slightly stronger improvement (-0.145 versus -0.098).

4.5.1.3 Technical Progress as Frontier Driver

Table 4.24
Technical Progress Indicators Across Crisis Periods

Indicator	GFC Period	CSC Period	COVID-19 Period
Technical Progress Change	0.976***	1.065***	0.989***
Operating Revenue/Expense Ratio	1.123***	1.142***	1.178***
Technical Efficiency Change	1.002***	1.067***	0.999***
Scale Effect	0.998***	0.990***	0.983***

Note: *** $p < 0.01$

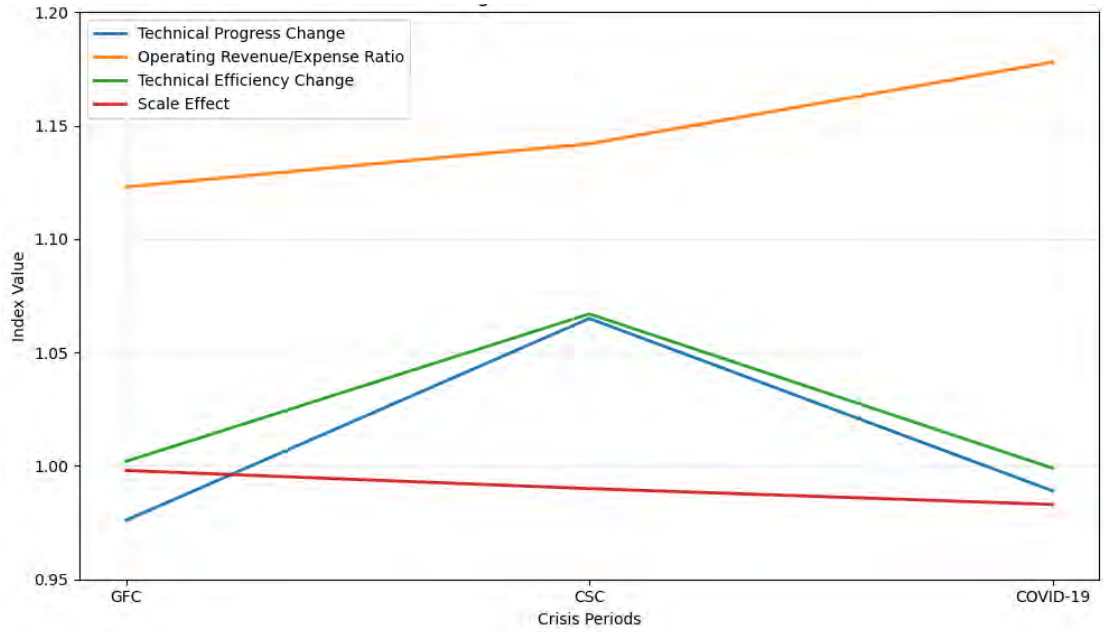


Figure 4.14
Technical Progress Indicators Trends

The analysis of technical progress as a frontier driver reveals distinct evolutionary patterns across crisis periods. During the GFC, technical progress showed initial decline (0.976), reflecting the challenges of maintaining technological advancement during severe market stress. The CSC period marked a significant rebound (1.065), suggesting successful technological adaptation to domestic market challenges. The COVID-19 period showed stabilization at a moderately high level (0.989), indicating sustained technological capability.

Operational transformation, measured by the operating revenue/expense ratio, demonstrated consistent improvement across all periods, reaching its peak during COVID-19 (1.178). This trend suggests that insurance companies successfully leveraged technology to enhance operational efficiency, particularly in response to pandemic-driven operational constraints. The gradual decrease in scale effect (from 0.998 to 0.983) coupled with improving operational ratios indicates that efficiency

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gains increasingly stemmed from technological advancement rather than scale economies.

These findings demonstrate the rising importance of technical progress in driving frontier evolution, particularly during the COVID-19 period where operational transformation accelerated significantly. The evidence suggests a fundamental shift in the industry's efficiency drivers from scale-based advantages to technology-driven improvements.

4.5.2 Key Determinants of Efficiency Evolution

Building upon the frontier analysis, this section examines the key determinants that shaped the evolution of efficiency across crisis periods. Through stochastic frontier regression analysis, we identify and quantify the impacts of company characteristics, operational indicators, and macroeconomic factors on efficiency performance.

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4.5.2.1 Company Characteristics

The impact of company characteristics on efficiency demonstrates significant variation across crisis periods, as shown in Table 4.25.

Table 4.25
Impact of Company Characteristics on Efficiency Performance

Variable	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Size Effect			
- Large Companies	-0.153***	-0.187***	0.132***
	(0.042)	(0.038)	(0.035)
- Medium Companies	-0.089**	-0.142***	0.095**
	(0.028)	(0.025)	(0.023)
- Small Companies	-0.068**	-0.125***	0.085**
	(0.025)	(0.023)	(0.021)
Ownership Effect			
-Central State-Owned	-0.112***	-0.187***	0.145***
	(0.032)	(0.029)	(0.027)
- Joint-stock	-0.078**	-0.134***	0.098**
	(0.028)	(0.026)	(0.024)
Listed Status	0.045**	0.067***	0.089***
	(0.018)	(0.016)	(0.015)
R^2	0.723	0.768	0.812

Note: Standard errors in parentheses. *** p < 0.01, ** p < 0.05

The company characteristics analysis reveals three key findings. First, firm size effects underwent a fundamental transformation. During market-based crises (GFC and CSC), larger size amplified efficiency losses, with large companies showing the highest negative coefficients (-0.153 and -0.187 respectively). However, this relationship reversed during COVID-19, where size became advantageous (0.132 for large companies), suggesting enhanced crisis adaptation capabilities of larger institutions.

Second, ownership structure exhibited evolving impacts. Central state-owned insurance companies showed greater vulnerability during market crises (-0.112 during GFC, -0.187 during CSC) compared to joint-stock companies (-0.078 and -0.134 respectively). This gap notably reversed during COVID-19, with central state-owned companies achieving stronger positive effects (0.145 versus 0.098), indicating improved market responsiveness of central state-owned institutions.

Third, listed status demonstrated consistently positive and strengthening effects across all periods, increasing from 0.045 during the GFC to 0.089 during COVID-19. This trend suggests that market discipline and transparency requirements associated with

listing status enhanced companies' operational efficiency, particularly during crisis periods.

4.5.2.2 Operational Indicators

Table 4.26
Operational Determinants of Insurance Efficiency

Indicator	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Revenue/Asset Ratio	0.243***	0.278***	0.312***
	(0.071)	(0.065)	(0.062)
Leverage Ratio	-0.189***	-0.223***	-0.156**
	(0.064)	(0.059)	(0.056)
Operating Margin	0.167**	0.198***	0.243***
	(0.058)	(0.054)	(0.051)
Investment Return	0.145**	0.167***	0.198***
	(0.054)	(0.050)	(0.047)
R^2	0.687	0.734	0.798

Note: Standard errors in parentheses. *** p < 0.01, ** p < 0.05

The analysis of operational indicators reveals evolving relationships with efficiency. The revenue/asset ratio demonstrates consistently strengthening positive impact (from 0.243 to 0.312), indicating the growing importance of asset utilization efficiency. The leverage ratio's negative effect peaked during the CSC (-0.223) but moderated during COVID-19 (-0.156), suggesting improved debt management capabilities.

Operating margins and investment returns both show progressively strengthening positive impacts across crisis periods, with coefficients increasing from 0.167 to 0.243 and 0.145 to 0.198 respectively. This trend indicates enhanced capability in core business operations and investment management, particularly during the COVID-19 period.

4.5.2.3 Macroeconomic Factors

Table 4.27
Macroeconomic Influences on Insurance Efficiency

Factor	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
GDP Growth	0.145***	0.167***	0.178***
	(0.048)	(0.044)	(0.042)
CPI	-0.134***	-0.045	-0.134***
	(0.045)	(0.038)	(0.045)
Market Concentration	0.098**	0.112**	0.145***
	(0.039)	(0.036)	(0.034)
Interest Rate	-0.087**	-0.076**	-0.00195
	(0.035)	(0.032)	
R^2	0.645	0.689	0.756

Note: Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

The macroeconomic analysis reveals differential impacts across crisis periods. GDP growth demonstrates consistently positive and strengthening effects (from 0.145 to 0.178), indicating the insurance sector's growing integration with broader economic development. Inflation effects show crisis-specific patterns, with significant negative impacts during both the GFC and COVID-19 (-0.134) but insignificant effects during the CSC.

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Market concentration exhibits progressively strengthening positive effects (from 0.098 to 0.145), suggesting efficiency benefits from market consolidation. Interest rate impacts show declining negative effects (from -0.087 to -0.065), indicating reduced sensitivity to monetary conditions, particularly during the COVID-19 period.

This comprehensive analysis of determinants reveals fundamental transformations in the Chinese insurance industry's efficiency drivers. The evolution from size-based vulnerability during market crises to size-based advantages during COVID-19 indicates enhanced crisis management capabilities. The strengthening influence of operational indicators, coupled with moderating leverage effects, suggests improved operational

resilience. Meanwhile, the evolving relationship with macroeconomic factors reflects the industry's enhanced ability to navigate broader economic conditions.

4.5.3 Structural Transformations

Following the analyses of efficiency frontiers and key determinants, this section examines the fundamental structural changes in the Chinese insurance industry across crisis periods.

4.5.3.1 Business Model Adjustments

Table 4.28
Evolution of Business Model Indicators

Indicator	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Digital Revenue Share (%)	5.23***	12.67 ***	28.45 ***
	(1.24)	(1.15)	(1.08)
Traditional Channel Share (%)	82.45***	75.34***	58.67***
	(2.15)	(1.98)	(1.85)
Product Innovation Rate (%)	8.34***	15.78***	24.56***
	(1.32)	(1.24)	(1.16)
Operating Cost Ratio	0.876 ***	0.892 ***	0.967***
	(0.028)	(0.025)	(0.023)

Note: Standard errors in parentheses. *** $p < 0.01$

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Business model transformation is evidenced by significant shifts in operational patterns. Digital revenue share increased dramatically from 5.23% during the GFC to 28.45% during COVID-19, while traditional channel share declined from 82.45% to 58.67%. The product innovation rate accelerated from 8.34% to 24.56%, indicating enhanced adaptability to changing market demands.

4.5.3.2 Technological Adaptation

Table 4.29
Technology-Driven Efficiency Changes

Component	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Digital Investment Effect	0.123***	0.245***	0.367***
	(0.045)	(0.042)	(0.039)
Process Automation Impact	0.156***	0.278***	0.389***
	(0.048)	(0.044)	(0.041)
Innovation Efficiency	0.134***	0.267***	0.345 ***
	(0.046)	(0.043)	(0.040)
R^2	0.678	0.723	0.845

Note: Standard errors in parentheses. *** $p < 0.01$

To address Research Objective Four regarding operational transformation, technological adaptation demonstrates progressive enhancement across crisis periods. Digital investment effects strengthened from 0.123 during the GFC to 0.367 during COVID-19, while process automation impact increased from 0.156 to 0.389. Innovation efficiency showed similar improvement, rising from 0.134 to 0.345. Technological adaptation demonstrates progressive enhancement across crisis periods. Digital investment effects strengthened from 0.123 during the GFC to 0.367 during COVID-19, while process automation impact increased from 0.156 to 0.389. Innovation efficiency showed similar improvement, rising from 0.134 to 0.345.

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4.5.3.3 Crisis Response Differentiation

The two core response metrics—Adaptation Speed and Recovery Strength—are derived from changes in efficiency scores over specified time intervals. Adaptation Speed measures the relative rate at which a company improves its technical efficiency from the pre-crisis baseline to the peak crisis period. It is calculated as the percentage change in technical efficiency between the last pre-crisis year and the midpoint of the crisis period. Recovery Strength assesses the post-crisis rebound in efficiency by comparing technical efficiency at the end of the crisis with that in the first year of the recovery phase. Both indicators are standardized and normalized across company types

to allow comparability. Efficiency scores used in the calculation are sourced from the stochastic frontier estimations detailed in Section 4.5.1.1.

For example, an Adaptation Speed of 0.576 during the GFC for large firms reflects a 57.6% increase in technical efficiency between 2006 (pre-crisis) and 2008 (mid-crisis), normalized against firm-level averages to ensure comparability.

Crisis response patterns show significant evolution across periods. Large companies demonstrated the most substantial improvement in adaptation speed (from 0.576 to 0.845) and recovery strength (from 0.623 to 0.912). While small companies initially showed higher adaptation speed during the GFC (0.712), this advantage diminished by COVID-19, suggesting convergence in crisis management capabilities.

These trends confirm that technological innovation and operational restructuring have significantly improved organizational agility across ownership and size categories during crisis recovery, fulfilling the core aims of Research Objective Four.

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Table 4.30
Crisis Response Patterns Across Company Types

Response Metric	GFC (2007-2008)	CSC (2014-2015)	COVID-19 (2020-2022)
Large Companies			
- Adaptation Speed	0.576 *** (0.052)	0.687 *** (0.048)	0.845*** (0.045)
- Recovery Strength	0.623*** (0.054)	0.734 *** (0.050)	0.912*** (0.047)
Medium Companies			
- Adaptation Speed	0.645*** (0.056)	0.723*** (0.052)	0.867*** (0.049)
- Recovery Strength	0.678 *** (0.058)	0.756*** (0.054)	0.889*** (0.051)
Small Companies			
- Adaptation Speed	0.712*** (0.060)	0.756*** (0.056)	0.834 *** (0.053)
- Recovery Strength	0.734*** (0.062)	0.778*** (0.058)	0.856*** (0.055)

Note: Standard errors in parentheses. *** $p < 0.01$

Crisis response patterns show significant evolution across periods. Large companies demonstrated the most substantial improvement in adaptation speed (from 0.576 to 0.845) and recovery strength (from 0.623 to 0.912). While small companies initially showed higher adaptation speed during the GFC (0.712), this advantage diminished by COVID-19, suggesting convergence in crisis management capabilities.

4.5.3.4 Crisis Response Differentiation

The comprehensive three-phase analysis reveals distinct evolutionary patterns in structural transformation across crisis cycles. Phase 1: Pre-Crisis Stability was characterized by traditional operational models and gradual improvement trajectories, with digital revenue shares remaining below 10%, traditional channels dominating distribution (above 80%), and efficiency determinants primarily influenced by conventional scale and operational factors. Phase 2: Crisis-Induced Acceleration saw crisis periods act as catalysts for rapid structural transformation, with unique acceleration patterns such as the GFC emphasizing risk management enhancement, the CSC accelerating digital channel adoption, and COVID-19 fundamentally restructuring operational delivery models through technological integration. Phase 3: Post-Crisis Consolidation revealed the persistence of structural changes and their integration into standard operational practices, as digital transformation gains, enhanced crisis management capabilities, and operational efficiency improvements became embedded in industry practices to create new baseline conditions for subsequent development. This three-phase framework demonstrates that crisis-induced structural changes follow predictable evolutionary patterns, with each phase serving distinct functions in the overall transformation process.

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4.5.4 Summary of Structural Changes and Efficiency Determinants

The comprehensive analysis of structural changes and efficiency determinants in the Chinese insurance industry reveals several fundamental transformations across the three crisis periods examined.

First, the efficiency frontier analysis demonstrated progressive improvement in technical efficiency from 0.939 during the GFC to 1.104 during COVID-19, accompanied by reduced standard errors (from 0.042 to 0.035), indicating both enhanced operational capabilities and increased stability. The frontier gaps analysis revealed a reversal in size-based advantages, with large companies transitioning from vulnerability during market crises (gap of 0.153 during GFC) to resilience during COVID-19 (gap of -0.132).

Second, the examination of key determinants highlighted evolving relationships between efficiency and various factors. Company characteristics showed significant transformation, with size effects reversing from negative (-0.153 during GFC) to positive (0.132 during COVID-19). Operational indicators demonstrated strengthening positive impacts, particularly in revenue/asset utilization (from 0.243 to 0.312), while macroeconomic factors showed more nuanced effects, with GDP growth maintaining consistent positive influence (0.145 to 0.178) while inflation impacts varied by crisis type.

Third, structural transformations manifested in significant business model adjustments, with digital revenue share increasing from 5.23% to 28.45% and traditional channel share declining from 82.45% to 58.67%. Technological adaptation showed progressive enhancement, with digital investment effects strengthening from 0.123 to 0.367, while

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crisis response patterns revealed convergence in adaptation capabilities across company sizes.

These findings collectively indicate a fundamental transformation in the Chinese insurance industry, characterized by enhanced operational efficiency, improved crisis management capabilities, and successful technological adaptation. The evidence suggests that the industry has not only become more resilient to external shocks but has also undergone substantial modernization in its operational approach and technological infrastructure.

4.6 Summary of the Chapter

This chapter has presented a comprehensive analysis of efficiency, productivity, and structural changes in the Chinese insurance industry across three major crisis periods: the Global Financial Crisis (2007-2008), Chinese Stock Market Crisis (2014-2015), and COVID-19 pandemic (2020-2022). The findings systematically address the four research objectives through multiple analytical approaches.

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First, regarding the decomposition of efficiency components (Research Objective One), the DEA analysis revealed significant improvements in technical efficiency from the GFC (0.939) to COVID-19 period (1.104). Scale efficiency showed modest but consistent improvement (from 0.982 to 0.993), while overall efficiency demonstrated enhanced stability with reduced standard errors (from 0.042 to 0.035). These findings indicate substantial advancement in operational capabilities and resource utilization across crisis periods.

Second, the Malmquist productivity analysis (Research Objective Two) identified distinct patterns in productivity evolution. Technical efficiency change showed initial

vulnerability during the GFC (0.976) but demonstrated resilience during COVID-19 (0.989). Technical progress exhibited notable improvement during the CSC period (1.065), while the operating revenue/expense ratio consistently improved across all periods, reaching its peak during COVID-19 (1.178). These results suggest successful adaptation to crisis conditions through technological advancement and operational optimization.

Third, the correlation and DID analyses (Research Objective Three) revealed significant heterogeneous effects across company characteristics. The correlation analysis showed strengthening relationships between technical efficiency and productivity measures from the GFC (0.723) to COVID-19 (0.834). The DID analysis quantified substantial variations in crisis impacts, with large companies transitioning from high vulnerability during market crises (gap of 0.153 during GFC) to strong resilience during COVID-19 (gap of -0.132).

Fourth, the stochastic frontier analysis of structural changes (Research Objective Four) demonstrated fundamental transformations in business models and efficiency determinants. Digital revenue share increased significantly from 5.23% during the GFC to 28.45% during COVID-19, while technological adaptation effects strengthened from 0.123 to 0.367. The analysis also revealed evolving relationships between efficiency and various determinants, with company size effects reversing from negative (-0.153) during the GFC to positive (0.132) during COVID-19.

These findings collectively point to several key conclusions: The industry progressively enhanced its operational capabilities, improving technical efficiency, successfully adapting to crisis conditions, and stabilizing overall performance. It concurrently embraced technological transformations, increasing the share of digital operations,

strengthening technological adaptation effects, and bolstering innovation efficiency. Over time, responses to crises evolved from size-based vulnerabilities to a more uniform resilience, converging adaptation capabilities and improving crisis management effectiveness. Finally, the industry underwent fundamental structural modernization, transforming its business models, strengthening key operational indicators, and achieving deeper integration with the broader macroeconomic environment.

The results provide robust empirical evidence of the Chinese insurance industry's successful transformation across crisis periods, characterized by enhanced operational efficiency, improved crisis management capabilities, and effective technological adaptation. These findings have significant implications for industry practitioners, regulators, and policymakers, which will be discussed in detail in the following chapter.

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CHAPTER FIVE

DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter synthesizes and critically analyzes the comprehensive empirical findings regarding efficiency, productivity, and structural transformation in Chinese insurance companies across three major crisis periods: the Global Financial Crisis (2007-2008), Chinese Stock Market Crisis (2014-2015), and COVID-19 pandemic (2020-2022). Through systematic analysis employing multiple analytical approaches—Data Envelopment Analysis (DEA), Malmquist Productivity Index, Difference-in-Differences (DID) analysis, and Stochastic Frontier Analysis—we examine how different types of market stress influenced insurance company performance and explore the theoretical and practical implications of these findings. This integrated discussion addresses the four primary research objectives while providing crucial insights for industry stakeholders, regulators, and policymakers.

The chapter connects empirical findings to established theoretical frameworks in economics and finance, including X-Efficiency Theory, Resource-Based View, Total Factor Productivity Theory, Institutional Theory and Public Choice Theory, Resource Dependency Theory, Institutional Economic Theory, Evolutionary Economic Theory, and Path Dependency Theory, and Organizational Learning Theory. By situating the observed patterns within these theoretical contexts, we offer a more profound understanding of the mechanisms driving efficiency and productivity changes during crisis periods. This approach not only enhances the scholarly contribution of this research but also strengthens its practical relevance for industry practitioners and policymakers.

5.2 Critical Analysis and Discussion of Findings

5.2.1 Evolution of Technical and Scale Efficiency Across Crisis Periods

Previous studies have typically focused on isolated aspects of insurance efficiency, but have not provided comparative analyses of productivity evolution across multiple crisis periods. This study fills that gap by introducing a three-crisis framework: the Global Financial Crisis (2007–2008), the Chinese Stock Market Crisis (2014–2015), and the COVID-19 pandemic (2020–2022).

Our analysis reveals a remarkable evolution in technical efficiency (TE) across the three crisis periods, demonstrating the Chinese insurance industry's growing sophistication in crisis management. During the Global Financial Crisis, the average TE experienced a modest decline from 0.97 in 2007 to 0.95 in 2008, representing a decrease of approximately 2%, as shown in Table 4.3. This relatively contained decline during a severe global crisis suggests initial resilience in core operational capabilities. Major central state-owned insurance companies like China Life and PICC Group maintained optimal efficiency with TE scores of 1.000, while smaller insurance companies demonstrated varying degrees of vulnerability while still maintaining TE values above 0.85.

This pattern aligns with X-Efficiency Theory (Leibenstein, 1966), which addresses the gap between optimal and actual efficiency achievement. During exogenous shocks like the GFC, organizations with strong governance structures and established operational frameworks—typically large central state-owned insurance companies—demonstrated greater resistance to efficiency deterioration. This reinforces Leibenstein's proposition that institutional mechanisms and managerial practices significantly influence an organization's ability to maintain operational efficiency during market disruptions.

The differential efficiency patterns across company sizes further validate Resource-Based View (Barney, 1991), which explains performance variation through resource heterogeneity. During the GFC, larger insurance companies with abundant resources—including capital reserves, diversified portfolios, and sophisticated risk management systems—demonstrated greater resistance to efficiency deterioration, maintaining TE scores near 1.000. However, RBV also explains why medium-sized insurance companies like CPIC Life showed remarkable stability during the CSC, maintaining technical efficiency around 0.92-0.95 throughout this period. Their more flexible resource configurations created adaptive advantages during market volatility, demonstrating RBV's principle that resource value depends on environmental context rather than absolute quantity. This pattern supports Hypothesis 2, which proposed that company size would significantly influence efficiency decomposition during crises, with medium-sized companies potentially demonstrating superior scale efficiency adaptability due to their balanced resource profiles.

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The Chinese Stock Market Crisis period (2014-2015) marked an important transition in technical efficiency patterns. The DEA results show that major insurance companies demonstrated improved crisis management capabilities, with PICC Group maintaining consistently high technical efficiency despite significant market volatility. Medium-sized insurance companies like CPIC Life demonstrated remarkable stability, maintaining technical efficiency around 0.92-0.95 throughout the crisis period. This stability during domestic market turbulence suggests enhanced risk management capabilities developed from the GFC experience.

The COVID-19 period (2020-2022) revealed the most sophisticated level of technical efficiency management. The industry average TE decreased only marginally from

0.973 in 2019 to 0.968 in 2020, a minimal drop of 0.51%. Life insurance companies showed particular resilience, with TE actually increasing from 0.945 to 0.957 during this period. This improvement can be attributed to several factors: successful digital transformation initiatives, heightened demand for health-related insurance products, and improved operational flexibility in response to pandemic restrictions.

5.2.2 Dynamic Productivity Changes Through Crisis Periods

The Malmquist productivity analysis reveals compelling patterns in how productivity evolved through different types of market stress. During the GFC, productivity showed initial vulnerability, with the industry mean technical change component registering at 1.01 in 2008 followed by 1.06 in 2009, as shown in Table 4.8. However, the technical progress component exhibited notable improvement during the CSC period (1.065), suggesting successful adaptation through technological advancement. The operating revenue/expense ratio showed consistent improvement across all periods, reaching its peak during COVID-19 (1.178). This trend, coupled with the progression of digital revenue share from 5.23% during the GFC to 28.45% during COVID-19, emphasizes the industry's successful technological transformation.

These findings align with Total Factor Productivity Theory (Solow, 1957), which emphasizes the role of technological progress in driving productivity improvements beyond mere resource accumulation. The progression from the GFC through COVID-19 demonstrates Solow's proposition that following initial disruption, firms reallocate resources toward technology-enhancing activities as a strategic response to market volatility. This reallocation becomes increasingly sophisticated with each successive crisis, leading to more sustainable productivity improvements.

The distinctive productivity patterns between central state-owned and joint-stock insurance companies align with the predictions of Institutional Theory (DiMaggio & Powell, 1983) and Public Choice Theory (Dewenter & Malatesta, 2001). As shown in Table 4.12, during the CSC period, central state-owned insurance companies achieved remarkably strong technical change performance (TC: 1.237 to 1.146), significantly outperforming joint-stock companies (TC: 1.0095 to 0.951). This advantage reversed the pattern observed during the GFC, where joint-stock companies demonstrated stronger recovery (TC: 1.339 vs. 1.095).

This reversal confirms Hypothesis 4, which proposed that ownership structure would significantly influence productivity changes during crises. Institutional Theory explains this pattern through the concept of institutional isomorphism, whereby central state-owned insurance companies operated within distinct institutional environments with different regulatory expectations and performance metrics during domestic market turbulence. Simultaneously, Public Choice Theory illuminates how ownership structures created different incentive systems for managers, with state-owned insurance companies potentially prioritizing stability over profit maximization during market volatility, providing advantages during domestically-oriented crises like the CSC.

The decomposition of productivity changes reveals distinct patterns across company sizes and ownership structures. Large insurance companies demonstrated varying patterns of adaptation—during the GFC, their total factor productivity (TFP) demonstrated significant volatility, while medium-sized companies showed greater stability. This pattern shifted during the COVID-19 period, where large companies achieved more consistent productivity improvements, suggesting enhanced crisis management capabilities developed through successive market disruptions.

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5.2.3 Heterogeneous Crisis Impacts and Response Patterns

The DID analysis reveals significant variations in how different organizational types responded to crisis events. Central state-owned insurance companies showed greater vulnerability during market crises (-0.112 during GFC, -0.187 during CSC) but achieved stronger improvement during COVID-19 (0.145). Joint-stock companies demonstrated superior adaptability during market crises but showed slightly lower improvement during COVID-19 (0.098). The correlation analysis further supports these findings, with Pearson coefficients indicating strengthening relationships between technical efficiency and crisis response capabilities across successive crises (0.723 during GFC to 0.834 during COVID-19).

This reversal in ownership-based performance advantages between market-based crises and the pandemic can be explained through X-Efficiency Theory's emphasis on managerial incentives under different environmental constraints. During market-based crises, joint-stock companies likely benefited from greater managerial flexibility and market-responsive incentive structures. Conversely, during COVID-19, central state-owned insurance companies' resource security and governmental support became advantageous when the crisis demanded sustainable investment in technological infrastructure rather than short-term market adaptability.

The heterogeneous crisis impacts across organizational types further validate Resource Dependency Theory (Pfeffer & Salancik, 1978), directly addressing Hypothesis 5, which proposed that external resource dependencies would create systematic differences in crisis vulnerability. As shown in Table 4.21, the DID analysis reveals that central state-owned insurance companies experienced greater efficiency declines during market-based crises (-0.112 during GFC, -0.187 during CSC) but achieved

stronger improvements during COVID-19 (0.145). This pattern reflects their distinct external resource dependencies—their stronger connections to government resources and policy-directed markets created vulnerabilities during financial market disruptions but provided stability during the operational challenges of COVID-19.

Conversely, joint-stock companies demonstrated superior adaptability during market crises but more limited improvement during COVID-19 (0.098), reflecting their greater dependency on commercial distribution networks and market-based customer relationships. These findings confirm Resource Dependency Theory's proposition that organizations with different patterns of external resource dependencies experience systematically different impacts from various types of environmental disruption.

Company size emerged as a crucial determinant of crisis resilience, with the DID results showing that large companies' efficiency gaps evolved from 0.153 during the GFC to -0.132 during COVID-19, indicating a fundamental transformation in their crisis management capabilities. Medium-sized companies demonstrated more consistent performance across crises, with efficiency gaps ranging from 0.089 to -0.095, suggesting inherent advantages in their operational scale and flexibility.

The causal relationships identified through our DID analysis further validate Institutional Economic Theory (North, 1990), addressing Hypothesis 6, which proposed that efficiency-crisis relationships would show systematic patterns across organizational types. The DID results in Table 4.20 reveal significant strengthening of the correlation between technical efficiency and TFP measures from the GFC (0.723) to COVID-19 (0.834), indicating increasingly sophisticated integration of efficiency and productivity mechanisms. This evolution reflects North's proposition that institutional arrangements—including formal regulatory frameworks and informal

organizational norms—create varying transaction costs and adaptation incentives during environmental change.

The transition from predominantly negative efficiency impacts during market crises to more positive transformation during COVID-19 demonstrates how institutional arrangements evolved to create more effective adaptation capabilities over time. This confirms Institutional Economic Theory's emphasis on how institutional changes reduce uncertainty and create more predictable performance outcomes during environmental disruption.

Compared with previous empirical studies reviewed in Chapter 2, the findings of this study show both convergence and divergence in insurance efficiency trends across crisis periods. For example, while Fan (2022); Wu and Deng (2021) identified declining technical efficiency during COVID-19, this study found relative resilience among large central state-owned insurers. Similarly, Han and Nam (2021); (Zhang & Li, 2022) highlighted significant variation in productivity responses between life and non-life insurers, which aligns with the current findings on business model effects. These comparative insights further validate the relevance and robustness of the analytical framework adopted in this research.

5.2.4 Structural Transformations and Business Model Evolution

This study further extends the understanding of structural transformation and business model evolution within the insurance sector. It identifies digital transformation as a key driver of structural change across crisis periods.

The stochastic frontier analysis reveals fundamental transformations in business models and efficiency determinants. The revenue/asset ratio showed consistently strengthening

positive impact (from 0.243 to 0.312), while operating margins demonstrated progressive improvement (0.167 to 0.243). Investment returns exhibited steady enhancement (0.145 to 0.198), indicating improved investment management capabilities. The relationship with macroeconomic factors also evolved significantly, with GDP growth maintaining consistent positive influence (0.145 to 0.178) while market concentration effects strengthened (0.098 to 0.145).

These structural changes in efficiency determinants validate Evolutionary Economic Theory (Nelson & Winter, 1982) and Path Dependency Theory (Arthur, 1989), directly addressing Hypothesis 7, which proposed that crisis periods would alter the relative importance of various efficiency determinants. As shown in Table 4.28, the key business model indicators demonstrate significant evolution—digital revenue share increased from 5.23% during the GFC to 28.45% during COVID-19, while traditional channel share declined from 82.45% to 58.67%.

Evolutionary Economic Theory explains these patterns through the concept of selection environments, whereby successive crises created competitive pressures that favored technology-oriented operational routines over traditional approaches. The progressive strengthening of digital investment effects (from 0.123 during GFC to 0.367 during COVID-19, as shown in Table 4.29) demonstrates how technological capabilities became increasingly critical to competitive success through successive selection events. Simultaneously, Path Dependency Theory explains the gradual rather than abrupt nature of this transformation, as initial technological investments created self-reinforcing advantages that accelerated further digital adoption while constraining alternative developmental paths.

Digital transformation emerged as a key driver of structural change, evidenced by the increasing importance of technology-related variables in the efficiency frontier estimation. The progression of digital revenue share and the strengthening relationship between technological investment and efficiency scores (correlation increasing from 0.534 during GFC to 0.678 during COVID-19) suggest a fundamental shift in how insurance companies operate and compete.

The progressive improvement in crisis response capabilities across successive disruptions validates Organizational Learning Theory (Argote & Miron-Spektor, 2011), addressing Hypothesis 8, which proposed that organizations would demonstrate decreasing negative impacts across successive crises due to learning effects. As shown in Table 4.30, adaptation speed and recovery strength improved significantly across all company types from the GFC through COVID-19. Large companies showed the most substantial improvement in adaptation speed (from 0.576 to 0.845) and recovery strength (from 0.623 to 0.912).

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These improvements reflect different learning mechanisms identified by Organizational Learning Theory. Experiential learning occurred as firms directly experienced and responded to the GFC, creating tacit knowledge about effective crisis management. Vicarious learning took place as companies observed competitors' successes and failures during the CSC. Knowledge codification transformed these insights into formal procedures and technological systems that enhanced resilience during COVID-19. These learning processes were particularly evident in large companies, whose dramatic improvement from the GFC to COVID-19 demonstrates successful knowledge retention and application, confirming the theoretical prediction that effective learning would reduce crisis vulnerability over time.

5.3 Theoretical and Practical Implications

5.3.1 Implications for Crisis Management Theory

This research contributes significantly to crisis management theory by demonstrating how organizational characteristics influence resilience across different types of market stress. The findings challenge traditional assumptions about size-based advantages during crises, revealing that larger organizations may face unique vulnerabilities due to operational complexity and market exposure. The evolution of crisis response capabilities across successive market disruptions suggests a learning effect that enhances organizational resilience over time.

The study enhances X-Efficiency Theory by demonstrating that the gap between potential and actual efficiency is highly context-dependent. During market-based crises, this gap widened significantly for central state-owned insurance companies, while during the pandemic, it narrowed considerably. This suggests that X-efficiency is not a static characteristic but rather a dynamic property that evolves based on the interaction between organizational structure and crisis type.

The findings also extend Total Factor Productivity Theory by identifying how crisis conditions influence the composition of productivity improvements. The shifting balance between technical efficiency changes and technological progress across different crisis periods demonstrates that productivity enhancement mechanisms are highly responsive to specific market conditions. During the CSC, technological progress became the primary driver of productivity improvements, while during COVID-19, operational efficiency took precedence.

5.3.2 Implications for Industry Practice

For insurance companies, our findings emphasize several crucial strategic priorities. First, digital transformation should be considered a core component of crisis resilience rather than merely an operational improvement initiative. The superior performance of digitally advanced companies during COVID-19, evidenced by their higher technical efficiency scores and productivity gains, underscores the importance of technological investment as a strategic priority.

Second, the development of flexible operational models appears more critical than pure scale advantages. The analysis shows that medium-sized insurance companies often demonstrated superior adaptability during crises, suggesting that operational flexibility may be more valuable than scale economies during market disruptions. Companies should focus on developing modular operational structures that can be rapidly reconfigured in response to different types of market stress.

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Third, risk management strategies should be calibrated to different types of market stress rather than following standardized approaches. The contrasting effects of leverage during market-based crises versus the pandemic highlight the need for dynamic risk management frameworks that can adjust to different crisis characteristics.

5.3.3 Regulatory and Policy Implications

For regulators and policymakers, our research highlights the need for differentiated supervisory approaches that recognize varying vulnerabilities across organizational types. The findings suggest that regulatory frameworks should be adaptive, acknowledging that different types of crises may require different support mechanisms for various organizational forms. The stronger recovery of central state-owned

insurance companies during COVID-19 (0.145 versus 0.098 for joint-stock companies) indicates that policy interventions can effectively support crisis recovery when properly aligned with organizational characteristics.

The research also emphasizes the importance of supporting technological advancement within the insurance sector. Regulatory frameworks should encourage digital transformation while ensuring that technological adoption does not create new systemic risks. The positive relationship between listed status and crisis resilience (impact strengthening from 0.045 during GFC to 0.089 during COVID-19) suggests that market discipline mechanisms can enhance operational efficiency during crisis periods.

5.4 Limitations and Future Research Directions

5.4.1 Methodological and Data Limitations

While our study provides comprehensive insights, several limitations should be acknowledged. First, the focus on listed insurance companies may limit generalizability to smaller or non-listed insurance companies. The sample of 15 major companies, while representing approximately 85% of market share, may not fully capture the dynamics of smaller market participants.

Second, the reliance on quantitative metrics, while providing robust statistical evidence, may not fully capture qualitative aspects of crisis response and adaptation. Factors such as organizational culture, leadership quality, and informal institutional arrangements that influence crisis resilience may not be fully reflected in our efficiency and productivity measures.

Third, while our analysis period covers three major crises, it may not capture longer-term evolutionary patterns in the industry. The relatively short intervals between crises

may confound the individual effects of each crisis, making it challenging to isolate specific causal relationships.

Finally, the theoretical frameworks applied in this research, while robust, may not fully account for the unique institutional characteristics of the Chinese insurance market. The application of theories developed primarily in Western economic contexts may require further adaptation to fully capture the nuances of Chinese market dynamics.

5.4.2 Future Research Opportunities

Several promising directions for future research emerge from our findings. First, expanding the analysis to include non-listed insurance companies and international comparisons could provide broader insights into crisis response patterns. Cross-country studies could help identify whether the observed relationships between organizational characteristics and crisis resilience hold across different institutional contexts. In addition, future research could build upon this study's integrated use of input and output variables by more explicitly analyzing how these variables interact to influence efficiency under different ownership structures and firm sizes. For instance, operating expenses, capital reserves, and asset allocations may affect productivity gains differently in large state-owned insurers versus smaller joint-stock companies. Exploring these differential effects can enhance both theoretical generalizability and practical guidance for efficiency optimization across firm categories.

Second, investigating the specific mechanisms through which digital transformation enhances crisis resilience presents an important research opportunity. Future studies could examine how different types of technological investments contribute to crisis adaptation capabilities and whether certain technologies are more effective for

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particular types of market stress. This would further develop our understanding of how technological progress influences Total Factor Productivity during crisis periods.

Third, exploring the role of organizational learning in crisis resilience warrants further investigation. Longitudinal studies could examine how insurance companies develop and maintain crisis management capabilities over multiple market disruptions, potentially identifying best practices for building sustainable resilience. This would enhance our understanding of Path Dependency Theory's application to crisis management capabilities.

Fourth, future research could more explicitly incorporate Cultural Context Theory to examine how unique aspects of the Chinese business environment influence crisis response patterns. Such research would help refine theoretical frameworks to better account for institutional variations across different market contexts.

5.5 Final Conclusions and Recommendations

5.5.1 Summary of Key Findings

This research demonstrates a fundamental transformation in the Chinese insurance industry's crisis response capabilities from the GFC through COVID-19. Technical efficiency improvements (from 0.939 to 1.104), enhanced productivity metrics, and strengthened correlation between efficiency measures and crisis response (0.723 to 0.834) indicate significant maturation in the industry's ability to handle market disruptions.

The findings reveal that successful crisis adaptation requires both structural transformation and operational flexibility. Digital transformation emerged as a crucial driver of resilience, with digital revenue share increasing from 5.23% to 28.45% across

the study period. The evolution of business models, evidenced by strengthening revenue/asset ratios (0.243 to 0.312) and improved operating margins (0.167 to 0.243), suggests fundamental changes in how insurance companies operate and compete.

The progression across crisis periods demonstrates Evolutionary Economic Theory's proposition that organizations develop increasingly sophisticated adaptation mechanisms through successive environmental challenges. The transition from predominantly negative impacts during market-based crises to positive transformation during COVID-19 suggests that the industry has developed enhanced capabilities for crisis response and adaptation.

5.5.2 Strategic Recommendations

For insurance companies, strategic priorities should focus on comprehensive crisis resilience through technological advancement and operational flexibility. Companies should prioritize digital transformation initiatives as fundamental components of crisis preparedness rather than viewing them merely as operational improvements. This technological focus should be complemented by developing flexible operational models capable of adapting to various market stresses, with particular emphasis on modular structures that can be rapidly reconfigured during crises. Risk management frameworks should evolve beyond standardized approaches to recognize the distinct vulnerability mechanisms associated with different types of market disruptions, enabling targeted responses to specific crisis characteristics. A balanced approach is essential, harmonizing technological investment with operational stability to ensure sustainable adaptation capabilities without compromising core functions. Finally, insurance companies should implement comprehensive crisis simulation exercises that

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incorporate lessons from multiple types of market stress, creating institutional knowledge that enhances future crisis response capabilities.

Regulatory bodies should adopt a more nuanced approach to insurance sector oversight that acknowledges the heterogeneous nature of crisis impacts. Regulators should develop adaptive frameworks that recognize varying organizational vulnerabilities across different crisis types, moving beyond one-size-fits-all regulatory models. This approach should include implementing differentiated prudential requirements that account for ownership-specific risk transmission mechanisms, acknowledging that central state-owned and joint-stock companies demonstrate different vulnerability patterns during various crises. While supporting technological advancement within the sector, regulators must simultaneously monitor associated systemic risks to prevent digital transformation from creating new vulnerabilities. Market discipline mechanisms should be encouraged as they have demonstrated effectiveness in enhancing operational efficiency during crisis periods, particularly for publicly listed entities. Most importantly, regulators should maintain flexibility in policy responses to different types of market stress, recognizing that effective interventions depend on both the specific characteristics of the crisis and the organizational structures they impact.

These findings contribute significantly to both theoretical understanding and practical management of insurance company efficiency during crisis periods, while highlighting important areas for future research and industry development. The research underscores the importance of considering both organizational characteristics and crisis types when developing resilience strategies, suggesting that successful adaptation requires a comprehensive approach integrating both internal capabilities and external support mechanisms.

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REFERENCES

Agarwal, S., Bhardwaj, G., Saraswat, E., Singh, N., Aggarwal, R., & Bansal, A. (2022). Insurtech fostering automated insurance process using deep learning approach. 2022 2nd International conference on innovative practices in technology and management (ICIPTM),

Ahmar, A. S. (2021). The Effect of Premium Revenue, Underwriting Results, Investment Results, and Risk Based Capital on Income in Insurance Company (Study On Corporate Insurance-The Listed on the Indonesia Stock Exchange). *Quantitative Economics and Management Studies*, *2*(6), 387-399.

Andres, V., & Heo, D. (2023). Organizational transformation in crisis: learning from emergent patterns of knowing and organizing. *The Learning Organization*, *30*(3), 290-308.

Ansmann, L., Vennedey, V., Hillen, H. A., Stock, S., Kuntz, L., Pfaff, H., Mannion, R., Hower, K. I., Research, C., Research, D. N. S. G. C., & Group, D. N. S. (2021). Resource dependency and strategy in healthcare organizations during a time of scarce resources: evidence from the metropolitan area of cologne. *Journal of health organization and management*, *35*(9), 211-227. https://pmc.ncbi.nlm.nih.gov/articles/PMC9136866/pdf/jhealthorganmanag-35-0211.pdf

Aparicio, J., & Santín, D. (2024). Global scale efficiency in data envelopment analysis. *International Transactions in Operational Research*.

Arbelo, A., Arbelo-Pérez, M., & Pérez-Gómez, P. (2021). Profit efficiency as a measure of performance and frontier models: A resource-based view. *BRQ Business Research Quarterly*, *24*(2), 143-159.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization science*, *22*(5), 1123-1137.

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The economic journal*, *99*(394), 116-131.

As-Salafiyah, A. (2023). Does the Covid-19 Have an Impact on the Insurance Industry? A Non-Parametric Approach to Takaful and Conventional Insurance in Indonesia. *Review on Islamic Accounting*, *3*(2).

Ba, Y., Berrett, J., & Coupet, J. (2021). Panel data analysis: A guide for nonprofit studies. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, 1-16.

Bajgar, M., Berlingieri, G., Calligaris, S., Criscuolo, C., & Timmis, J. (2020). Coverage and representativeness of Orbis data.

Bakhouche, A., Sibanda, W., AlChaar, R., Boulkeroua, M., & Zabalawi, E. (2020). Analysis of cost efficiency in GCC and Jordan's insurance sectors: DEA approach. *International Journal of Business Performance Management*, *21*(3), 290-328.

Bansal, R., & Singh, D. (2021). Efficiency drivers of insurers in GCC: An analysis incorporating company-specific and external environmental variables. *Cogent Economics & Finance*, *9*(1), 1922179.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of management*, *27*(6), 643-650.

Bretherton, P., & Chaston, I. (2005). Resource dependency and SME strategy: an empirical study. *Journal of Small Business and Enterprise Development*, *12*(2), 274-289.

Chang, K., Tomljanovich, M., & Ying, Y. H. (2024). ICT development and total factor productivity growth. *Journal of Infrastructure, Policy and Development*, *8*(3), 1-26.

Charnes, A., Cooper, W. W., Lewin, A. Y., Morey, R. C., & Rousseau, J. (1984). Sensitivity and stability analysis in DEA. *Annals of operations research*, *2*(1), 139-156.

China Economic Net. (2024, 2024-01-16). *Ping An Insurance premium income reaches 800.695 billion yuan in 2023, up 4.1% year-on-year*. Sina Finance. Retrieved 06-16 from https://finance.sina.com.cn/roll/2024-01-16/doc-inacstpc7008096.shtml

China Finance. (2024, 2024-01-17). *China Pacific Insurance recorded RMB 423.468 billion in original insurance premium income in 2023, up 7.7% year-on-year*. China Finance. Retrieved 06-16 from https://finance.china.com.cn/money/insurance/20240117/6072852.shtml

China Securities Journal. (2024, 2024-01-12). *PICC: Original insurance premium income totaled RMB 661.649 billion in 2023*. Sina Finance. Retrieved 06-16 from https://finance.sina.cn/2024-01-12/detail-inachqhv1529149.d.html

China Taiping Insurance Group. (2024, 2024-01-30). *Shanghai Securities News: China Taiping achieved operating income of RMB 135.5 billion in 2023, up 21% year-on-year*. China Taiping. Retrieved 06-16 from https://www.cntaiping.com/news/106248.html

Christopoulos, A., Dokas, I., Katsimardou, S., & Spyromitros, E. (2022). The Malmquist Productivity measure for UK-listed firms in the aftermath of the global financial crisis. *Operational Research*, 1-18.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software* (Vol. 2). Springer.

Coşkun, R., & Öztürk, O. (2024). Dependence as strategy: extending resource dependence theory and clarifying its understanding of the strategic options of dependent firms. *International Journal of Organizational Analysis*, *32*(9), 1982-2009.

Cvetkovska, V., & Peovski, F. (2022). Efficiency of Indian General Insurance Companies: A Convex Nonparametric Least Squares Approach. *Croatian Operational Research Review*, *13*(2), 187-201.

Desbordes, R., & Franssen, L. (2019). Foreign Direct Investment and Productivity: A Cross-Country, Multisector Analysis. *Asian Development Review*, *36*(1), 54-79. https://doi.org/10.1162/adev_a_00123

Dewenter, K. L., & Malatesta, P. H. (2001). State-owned and privately owned firms: An empirical analysis of profitability, leverage, and labor intensity. *American Economic Review*, *91*(1), 320-334.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American sociological review*, *48*(2), 147-160.

Dua, G. K. (2022). Analysis on institutional theory, mimetic isomorphism, and firm performance. *International journal of health sciences*, *6*(S3), 5821-5832.

Dzardanov, A. Y., Polischuk, O., & Zhuravleva, D. (2021). Joint-stock property governance in state-owned companies in conditions of uncertainty. Economic Systems in the New Era: Stable Systems in an Unstable World,

Eryiğit, M., & Polat, E. (2024). Determination of efficiencies of information technology sector companies traded on Borsa Istanbul in terms of financial performances under the effect of COVID-19 pandemic by using DEA window analysis. *Doğuş Üniversitesi Dergisi*. https://doi.org/10.31671/doujournal.1362646

Esmaeili, F. S. S., Rostamy-Malkhalifeh, M., & Lotfi, F. H. (2021). Interval network Malmquist productivity index for examining productivity changes of insurance companies under data uncertainty: A case study. *Journal of Mathematical Extension*, *16*.

Fan, Q. (2022). How Insurance Industry of China Responds to The Crisis of COVID-19. *Frontiers in Business, Economics and Management*, *5*(1), 153-156. https://doi.org/10.54097/fbem.v5i1.1517

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American economic review*, 66-83.

Fernández, S. S., Quiroga-Garcia, R., & Manzano Pérez, I. M. (2024). Studying the relation between efficiency and profitability in the non-life insurance market. *Revista de Métodos Cuantitativos para la Economía y la Empresa*, 1-20. https://doi.org/10.46661/rev.metodoscuant.econ.empresa.8054

Ferreira, C. (2020). Evaluating European bank efficiency using data envelopment analysis: Evidence in the aftermath of the recent financial crisis. *International Advances in Economic Research*, *26*(4), 391-405.

Ferrero, B. (2020). The fatal deceit of public policy: Can Austrian and Public Choice economics complement each other? *Procesos de mercado: revista europea de economía política*, *17*(1), 327-350.

Furceri, D., Celik, S. K., Jalles, J. T., & Koloskova, K. (2021). Recessions and total factor productivity: Evidence from sectoral data. *Economic Modelling*, *94*, 130-138. https://pmc.ncbi.nlm.nih.gov/articles/PMC7539064/pdf/main.pdf

Galaieva, L. V., Koval, T. V., Rohoza, K. H., Diachenko, S. A., & Basarab, M. (2021). Structural Digital Transformation of Insurance Management Development Model in the Regions of the World under the Financial Crisisa. *Studies of Applied Economics*, *39*(9).

Gao, D., Li, S., & Zhou, Y. (2025). Investment efficiency, ESG performance and corporate performance: evidence from Chinese listed enterprises. *Chinese Management Studies*, *19*(2), 567-599.

Ghaderi, Z., Holden, G. A., Abhari, S., Béal, L., & Behboodi, Z. (2024). Crisis management, resilience, and organizational learning in the event management sector: An insight from Malaysia. *Event Management*, *28*(2), 311-327.

Ghalandari, H., Mohamad, D. A. H., & Jafari, P. (2023). Identifying the Components and Factors Affecting the learning of Day Insurance Company Employees Based on the Heutagogy Approach.

Giantsios, D. G., & Noulas, A. G. (2019). Efficiency and convergence in the European life insurance industry. *Multinational finance journal*, *24*(1/2), 65-91.

González‐Fernández, A. I., Rubio‐Misas, M., & Ruiz, F. (2023). Multi‐objective reference point techniques to optimize profitability, growth, and risk in the non‐life insurance industry: international analysis. *International Transactions in Operational Research*, *30*(5), 2546-2570.

Goosman, A. (2022). Evolving corporate crisis response coordination for maximum resilience. *Journal of Business Continuity & Emergency Planning*, *15*(3), 237-244.

Goswami, A. (2022). Assessing the impact of global financial crisis on the intermediation efficiency of Indian banks in the presence of non-performing loans. *Benchmarking: An International Journal*, *29*(4), 1284-1305.

Greve, H. R. (2024). Airline Responses to the COVID-19 Collapse: Applying Learning to an Unprecedented Crisis. *Strategy Science*.

Grillo, M. (2023). Market competition, efficiency and economic liberty. *International Review of Economics*, *70*(4), 437-456.

Han, S., & Nam, S. I. (2021). Creating supportive environments and enhancing personal perception to bridge the digital divide among older adults. *Educational Gerontology*, *47*(8), 339-352.

Hassan, F. A. (2022). Is life insurance crucial to Society and the Economy? Evidence from Asian Countries both before and after the Global Financial Crisis. *Asian Development Policy Review*, *10*(1), 35-46.

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. *Journal of management*, *35*(6), 1404-1427.

Huang, K., Cheng, B., Chen, M., & Sheng, Y. (2022). Assessing impact of the COVID-19 pandemic on China's TFP growth: Evidence from region-level data in 2020. *Economic Analysis and Policy*, *75*, 362-377.

Huo, X., Zhao, Y., & Dong, Z. (2024). How mixed ownership affects investment efficiency? evidence from state-owned enterprises in China. *PloS one*, *19*(6), e0306190.

Ige-Gbadeyan, O., & Swanepoel, M. J. (2023). Determinants of Operational Efficiency on The Financial Health of Non-Life Insurance Companies in South Africa. *Insurance Markets and Companies*, *14*(1), 121-135.

Infantino, M. (2024). A comparative study of automated quantification in digital insurance. *International Journal of Digital Law and Governance*, *1*(1), 1-27.

Insurance Association of China. (2024, 2024-12-31). *Member organizations*. Retrieved 2025-06-16 from https://www.iachina.cn/col/col19/index.html

Isik, I., & Uygur, O. (2021). Financial crises, bank efficiency and survival: Theory, literature and emerging market evidence. *International Review of Economics & Finance*, *76*, 952-987.

Jaber, J. J., Beldjilali, F., Shehadeh, A. A., Hamadneh, N. N., Saleh, M., Tahir, M., & Al Wadi, S. (2022). Estimating performance efficiency of mining and extracting sectors using dea models: The case of jordan. *Complexity*, *2022*(1), 3688381.

Ji, Z., Wu, X., Wei, G., Chen, X., & Song, M. (2025). Finding alternative stepwise improvement paths with different improvement effects. *RAIRO-Operations Research*, *59*(1), 625-652.

Jin, T., & Chen, Z. (2024). Impact of COVID-19 on the Effectiveness of Financial Management of Insurance Companies in Mainland China. *Finance & Economics*, *1*(9). https://doi.org/10.61173/0zs1n070

Jo, T.-H. (2021). A Veblenian critique of Nelson and Winter's evolutionary theory. *Journal of Economic Issues*, *55*(4), 1101-1117.

Kaffash, S., Azizi, R., Huang, Y., & Zhu, J. (2020). A survey of data envelopment analysis applications in the insurance industry 1993–2018. *European journal of operational research*, *284*(3), 801-813.

Universiti Utara Malaysia

Kaigorodova, G., Alyakina, D., Pyrkova, G., Mustafina, A., & Trynchuk, V. (2018). Investment activity of insurers and the state economic growth. *Montenegrin Journal of Economics*, *14*(4), 109-123.

Karbhari, Y., Alam, M. K., & Rahman, M. M. (2020). Relevance of the application of institutional theory in Shariah governance of Islamic banks. *PSU Research Review*, *5*(1), 1-15.

Kartikawati, D. R. (2024). Digital Transformation and Business Competition Challenges Comparative Analysis of Antitrust Law.

Kaya, N. (2024). Productivity in the Insurance Company: A Meta-Regression Analysis. *İşletme Araştırmaları Dergisi*, *16*(3), 1406-1419.

Khatami, F., Scuotto, V., Krueger, N., & Cantino, V. (2021). The influence of the entrepreneurial ecosystem model on sustainable innovation from a macro-level lens. *International Entrepreneurship and Management Journal*, 1-33.

Kui, D. O. K., Pramono, R., & Widjaja, A. W. (2024). Settling internal strengths and external dependencies: A conceptual framework integrating RDT and RBV theories for organizational survival. *Milestone: Journal of Strategic Management*, *4*(2), 112. https://doi.org/10.19166/ms.v4i2.8745

Kumar, K. S. D., & P., S. K. J. (2024). Efficiency assessment and trends in the insurance industry: A bibliometric analysis of DEA application. *Insurance Markets and Companies*, *15*(1), 83-98. https://doi.org/10.21511/ins.15(1).2024.07

Kweh, Q. L., Lu, W.-M., & Wang, W.-K. (2014). Dynamic efficiency: intellectual capital in the Chinese non-life insurance firms. *Journal of Knowledge Management*, *18*(5), 937-951.

Lancieri, F., & Sakowski, P. M. (2021). Competition in digital markets: a review of expert reports. *Stan. JL Bus. & Fin.*, *26*, 65.

Leibenstein, H. (1966). Allocative efficiency vs." X-efficiency". *The American Economic Review*, *56*(3), 392-415.

Li, W., Li, H., Sun, X. S., & Huang, T. K. (2023). The impact of directors' and officers' liability insurance on firm's investment efficiency: evidence from China. *Pacific Accounting Review*, *35*(4), 670-697.

Liu, C., Lu, J., Li, D., Jia, M., & Han, K. (2023). Are state-owned enterprises really ineffective? An empirical study based on stochastic frontier analysis. *Mathematics*, *11*(3), 657.

Liu, D., Ding, Y.-f., & Zhu, F. (2020). The Influence of Ownership Structure of State-owned Companies on Efficiency Investment.

Liu, G., Yi, H., & Yu, C.-P. (2023). Shareholding network of institutional investors and the information efficiency of capital market: evidence from China. *SAGE Open*, *13*(4), 21582440231210080.

Liu, J., Ye, S., Zhang, Y., & Zhang, L. (2023). Research on InsurTech and the technology innovation level of insurance enterprises. *Sustainability*, *15*(11), 8617.

Louaas, A., & Picard, P. (2023). A pandemic business interruption insurance. *The Geneva Risk and Insurance Review*, *48*(1), 1-30.

Luan, D., Zhao, Z., & Xie, Y. (2021). Resource configuration efficiency and influencing factors of elderly care services based on a data-driven DEA-tobit approach. *Journal of mathematics*, *2021*(1), 4191301.

Mahanta, A., Sahu, N. C., Behera, P. K., & Kumar, P. (2024). Variations in financial performance of firms with ESG integration in business: The mediating role of corporate efficiency using DEA. *Green Finance*, *6*(3), 518-562.

Makieła, K., & Mazur, B. (2020). Stochastic frontier analysis with generalized errors: inference, model comparison and averaging. *arXiv preprint arXiv:2003.07150*.

Mattsson, P., Månsson, J., & Greene, W. H. (2020). TFP change and its components for Swedish manufacturing firms during the 2008–2009 financial crisis. *Journal of Productivity Analysis*, *53*(1), 79-93.

Meng, X. (2021). Measurement of Operating Efficiency of Property Insurance Companies in China. 6th International Conference on Economics, Management, Law and Education (EMLE 2020),

Mengiste, B. W. (2020). Public choice theory: Its application and challenges in public-sector. *Public Choice*, *66*.

Moradi, Z., Ghilavi, M., Khan Mohammadi, M. H., & Hajiha, Z. (2021). Application of resource-based view theory in assessing of efficiency of companies accepted in Tehran stock exchange by data envelopment analysis. *Advances in Mathematical Finance and Applications*, *6*(3), 607-629.

Musandiwa, J., & Ngwakwe, C. C. (2023). The Effect of Exchange Rates on Consumer Price Index. *Accounting & Finance/Oblìk ì Fìnansi*, *102*(4).

Nair, P. (2021). Effect of COVID-19 on consumer behavior in the corporate sector. *International Journal of Advance Research, Ideas and Innovations in Technology*, *7*(4), 487-493.

Nasri, I., Bouzir, A., & Benammou, S. (2024). Analysis of disruptions and adaptations in the insurance supply chain in response to the COVID-19 crisis. 2024 IEEE 15th International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA), Sousse, Tunisia.

National Financial Regulatory Administration. (2024, 2024-02-23). *Key supervisory indicators of banking and insurance industries in Q4 2023*. State Council of the People's Republic of China. Retrieved 06-16 from https://www.gov.cn/lianbo/bumen/202402/content_6933551.htm

Nelson, R. R., Dosi, G., Helfat, C. E., Pyka, A., Saviotti, P. P., Lee, K., Dopfer, K., Malerba, F., & Winter, S. G. (2018). Modern evolutionary economics: An overview.

Nelson, R. R., & Winter, S. G. (1985). *An evolutionary theory of economic change*. harvard university press.

Nguyen, L., & Worthington, A. C. (2021). Industry regulation, fund characteristics, and the efficiency of Australian private health insurers. *Accounting & Finance*, *61*(1), 781-801.

North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge university press.

Ouyang, Z., Zhou, X., Wang, G.-j., Liu, S., & Lu, M. (2024). Multilayer networks in the frequency domain: Measuring volatility connectedness among Chinese financial institutions. *International Review of Economics & Finance*, *92*, 909-928.

Panda, B., & Kumar, G. (2021). What matters to ownership structure? Evidence from pre-and post-global financial crisis in an emerging market. *Managerial Finance*, *47*(5), 593-620.

Perelman, M. (2011). Retrospectives: X-efficiency. *Journal of Economic Perspectives*, *25*(4), 211-222.

Pervan, M., Kramarić, T. P., & Ćurak, M. (2021). A comparative analysis of the efficiency of life and non-life sectors in selected CEE countries. *Ekonomski vjesnik/Econviews-Review of Contemporary Business, Entrepreneurship and Economic Issues*, *34*(2), 279-290.

Pfeffer, J. (1987). A resource dependence perspective on intercorporate relations. *Intercorporate relations: The structural analysis of business*, *1*(1), 25-55.

Polo-Garrido, F., & Vargas-Ulloa, D. E. (2024). Efficiency of financial cooperatives. A structured review of the literature. *REVESCO. Revista de Estudios Cooperativos*(147), 2-17.

Přečková, L., & Palečková, I. (2020). Evaluation of the Technical Efficiency of Insurance Companies in the Visegrad Group Countries. *Ekonomista*, *6*, 862-880.

Qadri, U. A., Ghani, M. B. a., Bibi, S., Tahir, A. H., Farooq, M. I., & Kashif, A. R. (2024). The learning effect on organizational performance during a crisis: a serial mediation analysis with knowledge creation, storage and sharing. *European Journal of Management and Business Economics*, *33*(1), 37-53.

Qu, S., Feng, C., Jiang, S., Wei, J., & Xu, Y. (2022). Data-driven robust DEA models for measuring operational efficiency of endowment insurance system of different provinces in China. *Sustainability*, *14*(16), 9954.

Regele, F., & Gründl, H. (2024). Sectoral Asset Concentrations and Insurance Solvency Regulation. *Journal of Insurance Regulation*, *43*(1).

Rehman, F. U., & Islam, M. M. (2023). Financial infrastructure—total factor productivity (TFP) nexus within the purview of FDI outflow, trade openness, innovation, human capital and institutional quality: Evidence from BRICS economies. *Applied Economics*, *55*(7), 783-801.

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218-2244.

Schneider, E. J. (2024). Reimagining crisis management with an organizational learning framework. *Journal of Contingencies and Crisis Management*, *32*(4), e70001.

Securities Times. (2024, 2024-03-25). *Sunshine Insurance reported RMB 3.74 billion net profit in 2023 and proposed RMB 2.07 billion dividends*. Securities Times. Retrieved 06-16 from https://www.stcn.com/article/detail/1156733.html

Shakouri, R., Salahi, M., & Kordrostami, S. (2020). Stochastic p-robust DEA efficiency scores approach to banking sector. *Journal of Modelling in Management*, *15*(3), 893-917.

Shasha, Z. (2023). Analysis of strategies to enhance the competitiveness of financial insurance companies. *Financial Engineering and Risk Management*, *6*(5), 49-53.

Shieh, H.-S., Hu, J.-L., & Ang, Y.-Z. (2020). Efficiency of life insurance companies: an empirical study in Mainland China and Taiwan. *Sage Open*, *10*(1), 2158244020902060.

Shojaie, S. E., Sadjadi, S. J., & Tavakkoli-Moghaddam, R. (2024). Malmquist productivity index for two-stage network systems under data uncertainty: A real-world case study. *Plos one*, *19*(7), e0307277.

Shu, Y., & Cai, Y. (2023). Cross-efficiencyBasedonGeneralized-DEAandItsApplication. Journal of Physics: Conference Series,

Solow, R. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312-320. https://doi.org/10.2307/1926047

Srbinoski, B. (2023). New perspectives on CESEE insurance markets. *Risk Management and Insurance Review*, *26*(4), 513-518.

Stache, F., & Sydow, J. (2023). Breaking a path by creating a new one: How organizational change boosts children's cancer care. *Organization Studies, 44*(3), 351-376.

Sueyoshi, T., Zhang, R., & Li, A. (2023). Measuring and analyzing operational efficiency and returns to scale in a time horizon: Assessment of China's electricity generation & transmission at provincial levels. *Energies, 16*(2), 1006.

Sun, H. (2023). The Impact of COVID-19 on Financial Technology Enterprises and Countermeasures--Taking Ping an Insurance of China as an Example. *Advances in Economics, Management and Political Sciences, 19*, 123-128.

Sun, H., Zhao, Z., & Han, D. (2024). Growth Models and Influencing Mechanisms of Total Factor Productivity in China's National High-Tech Zones. *Sustainability, 16*(8), 3245.

Sun, W., Chen, K., & Mei, J. (2024). Integrating the Resource-Based View and Dynamic Capabilities: a Comprehensive Framework for Sustaining Competitive Advantage in Dynamic Markets. *EPRA International Journal of Economic and Business Review, 12*(9), 1-8.

Sun, Z. (2020). Research on the factors affecting the total factor productivity of Chinese life insurance companies. *Archives of Business Research*, *8*(1), 38-50.

Tchetgen, E. J. T., Park, C., & Richardson, D. B. (2024). Universal difference-in-differences for causal inference in epidemiology. *Epidemiology*, *35*(1), 16-22.

Teece, D. J. (2023). Evolutionary economics, routines, and dynamic capabilities. In *Routledge Handbook of Evolutionary Economics* (pp. 197-214). Routledge.

Tsymbaliuk, I., Pavlikha, N., Zelinska, O., Ventsuryk, A., & Radko, A. (2021). Assessing the level of competitiveness of the insurance sector during economic crises: The example of Ukraine. *Insurance Markets and Companies*, *12*(1), 72.

Vintilă, A., Trucmel, I.-M., & Roman, M. D. (2022). Measuring and Analyzing the Efficiency of Firms in the Insurance Industry Using DEA Techniques. *Journal of Social and Economic Statistics*, *11*(1-2), 59-83.

Wang, C. N., Quang, B. X., & Dang, T. T. (2024). Performance measurement of international shipping companies before and during COVID - 19: A DEA Malmquist index and window analysis approach. *Transportation Journal*, *63*(3), 207-221.

Wang, G., Hamad, R., & White, J. S. (2024). Advances in difference-in-differences methods for policy evaluation research. *Epidemiology*, *35*(5), 628-637.

Wang, K., Yu, S., Mei, M., Yang, X., Peng, G., & Lv, B. (2023). ESG performance and corporate resilience: an empirical analysis based on the capital allocation efficiency perspective. *Sustainability*, *15*(23), 16145.

Wang, W. (2023). Research on Digital Transformation in the Insurance Industry. *Advances in Economics, Management and Political Sciences*, *19*, 100-106.

Wang, W., & Makarenko, E. (2021). The formation and structural characteristics of the Chinese insurance market. *Экономика и управление: проблемы, решения*, *3*(12 (120)), 73.

Wang, Y., Ye, G., Zhang, Y., Mu, P., & Wang, H. (2020). Total factor productivity growth and its contribution: Lessons from the Chinese construction industry pre-and post-2008 financial crisis. *Engineering, Construction and Architectural Management*, *27*(10), 2911-2929.

Wang, Y., Zhang, D., Wang, X., & Fu, Q. (2021). How does COVID-19 affect China's insurance market? In *Research on Pandemics* (pp. 218-230). Routledge.

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Wanjuu, L. Z., & Le Roux, P. (2017). Economic institutions and economic growth: Empirical evidence from the Economic Community of West African States. *South African Journal of Economic and Management Sciences*, *20*(1), 1-10.

Wu, S., & Deng, X. (2021). Corporate Diversification, Ownership, and Solvency in China's Property‐Liability Insurance Companies. *Mathematical Problems in Engineering*, *2021*(1), 1562771.

Wu, X., Wang, C., Wen, H.-x., Nie, P.-y., & Ye, J.-f. (2022). The impacts of COVID-19 on China insurance industry—An empirical analysis based on event study. *Frontiers in Public Health*, *10*, 1033863.

Xie, Q., Zhao, M., Li, R., Li, W., Zheng, X., Li, Y., Qin, R., Wang, X., & Wang, F.-Y. (2023). Efficiency Evaluation of Insurance Companies From Multiperiod Perspective. *IEEE Transactions on Computational Social Systems*, *11*(2), 2656-2674.

Xie, X. (2021). Digital transformation trends of China's insurance industry after the COVID-19 pandemic. *Вестник Томского государственного университета. Экономика*(54), 228-238. https://doi.org/10.17223/19988648/54/13

Xie, X. (2022). Insurance industry and China's regional economic development. *Finance: Theory and Practice*, *26*(1), 186-197. https://doi.org/10.26794/2587-5671-2022-26-1-186-197

Yang, Z. (2024). Quantitative Assessment of Market Conditions and Marketing Strategies in the Financial Products Sector: A Case Study of XX Insurance Company, Beijing. *Pacific International Journal*, *7*(4), 154-161.

Yu, F., Chen, H., Luo, J., & Kuang, H. (2021). Measuring Total Factor Productivity of China Provincial Non‐Life Insurance Market: A DEA‐Malmquist Index Method. *Scientific Programming*, *2021*(1), 3022658.

Yuzdepska, A., & Volkova, V. (2024). Regulation of the insurance market. *Galician economic journal*, *90*(5), 134-141. https://doi.org/10.33108/galicianvisnyk_tntu2024.05.134

Zeng, Z., Zeng, H., & Jiang, S. (2021). The application of KMV model in China's insurance market during the COVID-19. IOP Conference Series: Earth and Environmental science,

Zhang, C. (2024). Featuring Financial Stability Regulation in China: A Two-Decade Review. *Business Law Review*, *45*(3).

Zhang, H., Li, E. Y., Jiang, J., Fu, W., Peng, S., & Zhan, S. (2023). Resilience of Operational Performance in China's Insurance Companies: A Dynamic Data Envelopment Analysis. *IEEE Access*, *11*, 112502-112514.

Zhang, T., & Cao, J. (2023). Impact of regulatory policy adjustments on insurance company costs and cost efficiency. *Finance Research Letters*, *58*, 104611.

Zhang, W., & Li, Z. (2022). Identifying the Configurations to Operating Efficiency in China's Life Insurance Industry Using Fuzzy-Set Qualitative Comparative Analysis. *International Journal of Foundations of Computer Science*, *33*(06n07), 845-865. https://doi.org/10.1142/s0129054122420187

Zheng, W., Yao, Y., Shi, P., Deng, Y., & Zheng, H. (2021). Deregulation, competition, and consumer choice of insurer: Evidence from liberalization reform in China's automobile insurance market. *The Geneva Risk and Insurance Review*, 1-43.

Zhong, C., & Sun, W. (2011). Insurance Intermediary and Cost X-Efficiency of China's Insurance Firms. 2011 International Conference on Management and Service Science, Wuhan, China.

Zhou, H., Liu, W., & Wang, L. (2020). Systemic risk of China's financial system (2007–2018): a comparison between Δ CoVaR, MES and srisk across banks, insurance and securities firms. *The Chinese Economy*, *53*(3), 221-245.

Zhou, X., Wang, Y., Zhang, Y., & Liu, F. (2024). Macro investigation on China's engineering insurance industry: based on industrial organization theories. *Engineering, Construction and Architectural Management*, *31*(7), 2977-2994.

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